Robots, Tools, and Jobs: Evidence from Brazilian Labor Markets*

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Abstract

What is the effect of robots and tools on employment and labor market inequality? Using natural language processing and an instrumental variable approach, we discover that robots have led to a sizable decrease in the employment and wages of low-skilled workers in operational occupations. However, tools–machines that complement labor–have led to an equally large reinstatement of these workers, increasing their employment and wages. Using a quantitative model, we find that the lower prices of robots and tools over the last 20 years have reduced labor market inequality and increased welfare without a significant effect on employment.

Key Words: robots, automation, tools, labor-saving, labor-augmenting

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1 Introduction

Technological progress has drastically reduced the cost of automation. Between 1995 and 2016, the price of industrial robots in Brazil has decreased by 40%, making automation increasingly affordable for firms.[1] This affordability has led to a surge in the adoption of robots in various industries, causing concern among economists and policymakers as a growing body of evidence has suggested that automation may lead to job losses.

However, technological progress has not only decreased the cost of labor-saving machines, such as robots, but has also caused a rapid decrease in the cost of labor-augmenting machines, such as tools. The price of imported power tools by Brazilian firms, for instance, decreased by 20% between 1995 and 2016.[2]

In this paper, we study theoretically, empirically, and quantitatively how robots and tools affect employment, labor market inequality, and welfare. We show that the drop in the price of tools has greatly mitigated the job losses from automation. Overall, the decrease in the price of robots and tools has led to a decrease in labor market inequality and an increase in welfare without a significant effect on employment.

We expand the model of Acemoglu and Restrepo (2020) to include tools, i.e., machines that complement workers in their tasks, to study conceptually how robots and tools jointly affect the labor market. In the model, firms produce by performing tasks with robots or with workers. Workers can be low-skilled, with tools as complements, or high-skilled. Because tools are complements to low-skilled workers, a decrease in the price of tools increases employment and decreases inequality. The degree to which robots and tools affect the labor market will depend on the particular parameters of the model, which we identify from the data.

There are two challenges in bringing the model to the data. The first challenge lies in identifying machines that complement versus substitute the tasks done by workers. There are 535 different machines being imported by firms, making it difficult to identify their relationship to labor. The literature studying the effect of automation has addressed this

[1]The price of industrial robots is measured by their import prices. Adachi et al. (2022) and Graetz and Michaels (2018) also show a sizable decrease in the international price of industrial robots.

[2]Power tools include chainsaws, bandsaws, and angle grinders, among many others. Power tools are hand-operated pieces of equipment.

challenge by limiting the focus to industrial robots, which minimizes misclassification errors but significantly restricts the scope of analysis.[3]

The second challenge is the need for plausible exogenous variation in the incentive to adopt these two machine types. The imports of machines, as with any other input, are affected by shocks to the local economy. If, for instance, a demand shock led firms to increase their demand for robots, we would not be able to separate the labor market effects of an increase in demand from the labor market effects of robots adoption.

To tackle the first challenge, we classify machines as robots or as tools, using natural language processing and detailed machine descriptions from administrative import data for Brazil. Inspired by Argente et al. (2020), we use the text similarity between machine descriptions and Wikipedia pages to classify machines. Wikipedia is the only source containing a description and uses of a broad set of industrial machines.[4] A machine is labeled a robot if it is more similar to Wikipedia articles that describe different automation technologies than to Wikipedia pages that describe industrial tools.

Several tests indicate that the text-driven machine classification is reasonable. First, the classification delivers intuitive results. The machines most associated with robots are "Industrial Robots" and other numerically controlled machines. The machines most associated with tools are an assortment of hand-operated pieces of equipment. Second, the words relevant to the classification algorithm are those that are directly associated with robots, such as "automatic" or "numeric," or those that are associated with the use of tools, such as "hand" and "operate." Third, when machines have words associated with robots, such as "automatic," strongly increases the probability of them being classified as such. At the same time, when machines have words associated with tools, such as "tool" or "operate," it increases the probability of them being classified as a tool. Finally, firms adopting machines classified as robots do not significantly change employment, while those adopting tools significantly increase it, which is similar to what Koch et al. (2021) found when studying industrial robot adoption on the firm level.

We address the identification challenge by using tariff changes at the machine level as

[3]Industrial robots are classification number 8479 of the Harmonized System (HS). Therefore, the literature has focused on 0.5% of machines, which corresponds to 3% of all capital imports in 2019.

[4]Argente et al. (2020) use Wikipedia pages to classify patents of different products.

instruments for their adoption. Tariffs affect the final price of foreign machines and are unrelated to labor market shocks.[5] The identifying assumption is that changes in tariffs on robots and tools are orthogonal to labor market shocks. There are several pieces of evidence supporting this assumption. First, tariffs are not correlated with past labor market trends. Second, tariff changes are not correlated with campaign contributions, showing that political meddling on the determination of tariffs is unlikely. Third, tariffs are not correlated with other relevant policies of the period, such as subsidized loans or federal procurement. These results support the idea that tariffs on machines are not correlated with other shocks in the period.

We find that tools increase the employment and wages of low-skilled workers who operate machinery. Increasing the imports of tools by 1% would increase the employment and wages of low-skilled workers by 0.17% and 0.04%, respectively, without any effect on high-skilled workers. The effect of tools is larger on operational and technical workers, i.e., workers who directly operate machinery.

Robots, meanwhile, cause large disruptions in the labor market. A 1% increase in robot adoption decreases employment by 0.22%, an effect larger than what others have previously found.[6] As is the case with tools, the effect of robots is concentrated on low-skilled workers in operational occupations. These results suggest that if the adoption of tools and adoption of robots increase by the same amount, the effect on employment would not be statistically different from zero.

The identified effect of robots on employment is larger than previously found due to endogeneity in the traditional specification. The scale effect from the adoption of robots also leads to an increase in the adoption of tools. Failing to control for tools, as in previous work, leads to omitted variable bias, in which case, the parameter identified is only the effect of robots net of the effect of tools. Because tools increase employment, the estimate is upward-biased.

[5]Dix-Carneiro and Kovak (2017) use similar variation to study the effect of tariffs on Brazilian labor markets. As they discuss, tariffs in different products have changed at different rates. To isolate the effect of tariffs on machines, we control for tariffs on the final good and other inputs of each sector.

[6]Acemoglu and Restrepo (2020) find that a 1% increase in robot adoption would decrease employment by 0.03%. Dauth et al. (2021), Rodrigo (2022), and Graetz and Michaels (2018) do not find any effect of robots on employment.

To move from the relative effects identified in the data to aggregate effects, we build a quantitative model calibrated to reproduce the empirical findings. Firms and workers are located across regions and sectors. Firms choose between adopting robots to replace workers and using tools to complement them. Robots require the hiring of high-skilled workers to operate them. Firms use inputs from various sectors and sell products domestically or internationally. There is a capital-producing sector that produces robots and tools using final goods and imports of capital. Workers choose their skill level, region, and sector of employment, or to be outside the labor force. We calibrate key model parameters to replicate the observed effect of robots and tools on the labor market.[7]

Decreases in the prices of robots and tools over the last 20 years have increased welfare and reduced inequality without significant consequences for employment, according to the model. Imported robot and tool prices have dropped by 49.4% and 42.3%, respectively. Employment has remained stable because increased robot adoption has been counterbalanced by cheaper tools. Lower capital costs have enabled firms to cut final goods prices, boosting production and welfare. In addition, since tools complement low-skilled workers, the skill premium has decreased by 6%.

A welfare maximizing government should tax robots and subsidize tools. An increase in robot adoption increases productivity and aggregate consumption. But, because they reduce demand for low-skill workers, a tax on robots works as a transfer to the bottom of the income distribution, which increases total welfare.

Our main contribution is to add a broader set of machines to the standard theoretical, empirical, and quantitative framework for studying automation, leading to new conclusions and policy implications. Graetz and Michaels (2018) and Acemoglu and Restrepo (2020) were the first papers to study the effect of automation technologies on the labor market. They showed that the increase in automation led to a decrease in employment and wages. After their seminal work, several economists have expanded their analyses to study the effect of automation at the firm level (Koch et al. (2021), Humlum (2021), Acemoglu et al. (2020), Bonfiglioli et al. (2020), Bessen et al. (2019), Hubmer and Restrepo (2021)), in other

[7]The model builds on Artuç et al. (2010), Dix-Carneiro (2014), Caliendo et al. (2019), and Kleinman et al. (2023).

countries (Adachi et al. (2022), Rodrigo (2022), Kugler et al. (2020), Cheng et al. (2021), Cette et al. (2021), Dauth et al. (2021)), in different educational groups (Bonfiglioli et al. (2020)), and on inequality (Adachi (2022), Acemoglu and Restrepo (2022), Bonfiglioli et al. (2021)). Exploiting the geographical concentration of robot production in a few countries, several papers have used import data to measure the degree of automation of different sectors and firms, such as Humlum (2021), Bonfiglioli et al. (2020), and Rodrigo (2022). While the effect of automation at the firm level is up for debate, there is overwhelming evidence that robots decrease employment and wages at the market level.

We make several contributions to the automation literature. First, we expand the scope of the literature studying automation beyond industrial robots, which represent only 3% of capital imports in Brazil in 2019. We do so by classifying machines using text analysis into technologies associated to automation or those that complement workers. Second, we add tools and worker inequality to the canonical framework of Acemoglu and Restrepo (2020), which enables us to study how developments in machines that complement workers in their tasks affect the labor market.

Our most important contribution is highlighting that previous research has underestimated the impact of robots on the labor market by not controlling for the associated increase in the adoption of tools. This estimation bias may explain why some studies have found no effect of robots on employment (Graetz and Michaels (2018),Rodrigo (2022), Kugler et al. (2020), among others), while others have found a negative effect (Acemoglu and Restrepo (2020)).

This paper is also related to the literature studying the effects of automation using patents as proxy. Webb (2019) estimates the exposure of different occupations to robots using text similarity between patents and task descriptions. They find that increased exposure to robot patents is associated to a decline in employment and wages. Dechezleprêtre et al. (2021) identify patents related to automation machinery using key words. They find that an increase in low-skill wages leads to the creation of more automation technology. Mann and Püttmann (2023) classify patents between automation or non-automation using machine learning in a sample of 560 manually classified patents. They find that exposure to automation patents decrease manufacturing employment but increases service sector employment. Kogan et al.

(2023), written in parallel to our paper, uses the similarity of patents to task descriptions to classify them as labor-saving or labor-augmenting. They find that both technology types lead to a decrease in employment and wages.

We contribute to this literature by providing a direct measure of exposure of markets to machinery and by providing a new method to classify technologies. Machine adoption provides a direct measure of exposure of markets to labor-saving or labor-augmenting technologies. Firms that develop automation patents do not necessarily adopt these technologies. Due to the difficulty of linking patents to particular firms or labor market, the relationship between patents and labor-market outcomes is noisy at best. Using machines instead of patents, we present a more accurate measure of exposure to technology adoption because we observe the sectors and regions adopting these technologies.

We also contribute to this literature by proposing an alternative method of classifying machines. We classify machines as robots or tools according to the text similarity of these machines to the description of different automation technologies and industrial tools.

This paper is also related to the literature studying the relation between capital and labor. Most of the literature has found that capital embodied technological progress has led to an increase in inequality (Goldin and Katz 1998,Krusell et al. 2000,Autor et al. 2003,Hornstein et al. 2005) and decreased the labor share (Karabarbounis and Neiman 2013). Caunedo et al. (2023) allows for rich heterogeneity on how different capital types affect workers. We contribute to this literature by showing that the effect of capital on labor varies according to the type of capital using credible exogenous variation coming from variation on the import price of machines.

The paper is organized as follows. Section 2 discusses the simple model. Section 3 discusses the data. Section 4 discusses the machine classification. Section 5 describes the empirical specifications and Section 6 presents the empirical results. Section 7 lays out the quantitative model. Section 8 describes the parameter estimation and Section 9 presents the quantitative results. Section 10 concludes.

2 Simple Model

In this section, we study a simple model to understand how tools and robots affect the labor market. The model generates implications for the effect of cheaper robots and tools on the labor market, which are later tested in the data. We make three contributions to the canonical framework of Acemoglu and Restrepo (2020). First, we add tools, a capital type that complement workers in their tasks. Second, we add worker heterogeneity, which enables us to discuss inequality. Third, we find intuitive closed-form solutions by assuming a functional form for the relative productivity of robots.

The model provides three main takeaways. First, a decrease in the price of tools increases the employment of low-skilled workers due to, among other factors, the complementarity between low-skilled workers and tools. Second, the effect of tools on high-skilled workers is uncertain because high-skilled workers and tools are substitutes. Third, an increase in the adoption of robots increases inequality, whereas an increase in the adoption of tools decreases it. In the next section, we test these predictions on the data.

2.1 Model Setup

Environment. The model represents a small open economy. There are two sectors: one with tasks that can be automated and another that cannot be easily automated.[8] The automatable sector contains a representative firm, which performs a set of tasks to produce. Production of each task can be performed by either robots or by workers using tools. There are two types of workers. Low-skilled workers operate tools to produce, while high-skilled workers manage low-skilled workers in particular tasks. Robots and tools are imported and their prices, P_R and P_T, are exogenous.[9] Wages of high- and low-skilled workers, w_H and w_L, are determined endogenously.

[8]The relevant assumption for our results is that there are different sectors with different share of tasks that can be automated. To keep the model elegantly simple, we assume only two sectors with one of them not being able to use robots. In the quantitative model, we relax this assumption allowing for several sectors with different degrees of automatability.

[9]Throughout this section, we assume that both robots and tools are imported, and that the country is a small open economy. Therefore, both robot and tool prices are taken as given by the representative firm and are not affected by domestic demand. In the quantitative model that we introduce in Section 7, both types of capital are produced both abroad and domestically.

Total output is an aggregate of the automatable and non-automatable sectors

$$Y = \left(Y_A^{\frac{\psi-1}{\psi}} + Y_N^{\frac{\psi-1}{\psi}} \right)^{\frac{\psi}{\psi-1}},$$

where Y_A is production in the automatable sector, Y_N is production in the non-automatable sector, and ψ is the elasticity of substitution. We assume, as usual, that $\psi > 1$.

Representative Firm and Tasks. Output in the automatable sector is given by combining production from a continuum of tasks $\nu \in [0,1]$.[10] The production function in the automatable sector is:

$$Y_A = \left(\int_0^1 [y(\nu)]^{\frac{\lambda-1}{\lambda}} \, d\nu \right)^{\frac{\lambda}{\lambda-1}}, \tag{1}$$

where $y(\nu)$ is the output in task ν and λ is the elasticity of substitution between tasks.

Robots or Tools. Each task ν can be performed either by robots or by workers using tools:

$$y(\nu) = y_R(\nu) + y_T(\nu), \tag{2}$$

where $y_R(\nu)$ and $y_T(\nu)$ are the output of task ν using robots or tools, respectively.[11] The production function of task ν with robots is:

$$y_R(\nu) = Z_R(\nu) k_R(\nu), \tag{3}$$

where $Z_R(\nu)$ is the productivity of using robots in task ν, and $k_R(\nu)$ denotes the quantity of robots. The price of robots is given by P_R. Consequently, the marginal cost of completing task ν with robots is $\frac{P_R}{Z_R(\nu)}$.

Task ν can also be completed with workers and tools. If task ν is performed by workers,

[10] We assume that there is a representative firm in the automatable sector.

[11] Motivated by the empirical results to follow, we assume that robots do not require high-skill workers. In Section 6, we show that the empirical results are consistent with this assumption. In the quantitatie model, we relax this assumption and show that this margin is not quantitatively relevant.

output is given by:

$$y_T(\nu) = Z_T(\nu) \left[(\ell_H(\nu))^{\frac{\sigma-1}{\sigma}} + \left((\ell_L(\nu))^{\delta} (k_T(\nu))^{1-\delta} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{4}$$

where $Z_T(\nu)$ is the productivity of using tools for task ν, $\ell_L(\nu)$ is the number of low-skilled workers in each task, $\ell_H(\nu)$ is the number of high-skilled workers managing workers in task ν, and $k_T(\nu)$ is the quantity of tools. To facilitate exposition, and following a plethora of empirical evidence, we assume that low- and high-skilled workers are substitutes: $\sigma > 1$.[12]

We assume that low-skilled workers and tools are complements with Cobb-Douglas coefficient δ. This assumption is based on the observation that most tools, such as drill presses, mechanical lathes, welding machines, and other industrial physically intensive equipment, are operated by low-skilled workers. Moreover, as will be clear in the empirical section, this assumption rationalizes the positive effect of tool adoption on the employment of low-skilled workers.

If task ν is performed by workers and tools, the marginal cost is given by

$$\frac{\Theta_T}{Z_T(\nu)} = \frac{\left((w_H)^{1-\sigma} + \left(w_L^{\delta} P_T^{1-\delta} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}}{Z_T(\nu)},$$

where w_H is the wage of high-skilled workers, w_L is the wage of low-skilled workers, and P_T is the price of tools.

The marginal cost to complete task ν is

$$c(\nu) = \min \left\{ \frac{P_R}{Z_R(\nu)}, \frac{\Theta_T}{Z_T(\nu)} \right\}.$$

Task Heterogeneity. Tasks are heterogeneous in the relative productivity of robots and tools. The productivity follow an i.i.d. Fréchet distribution across tasks (ν) and technologies (l):

$$F_{Z_l(\nu)}(z) = \exp\left[-T_l \times z^{-\theta} \right], l \in \{R, T\}.$$

[12]See Katz and Murphy (1992), Krusell et al. (2000), and Ciccone and Peri (2005).

θ, the shape parameter, serves as the elasticity of substitution between technologies.[13] T_l, the scale parameter, determines the mean relative productivity.

Expenditure Share and Production. The expenditure share on tasks performed with technology $l \in \{R, T\}$ is

$$\pi_l = \frac{T_l(\Theta_l)^{-\theta}}{T_R(P_R)^{-\theta} + T_T(\Theta_T)^{-\theta}}.$$

The economy's total expenditure on tasks performed with technology l is:

$$X_l = \frac{T_l(\Theta_l)^{-\theta}}{T_R(P_R)^{-\theta} + T_T(\Theta_T)^{-\theta}} \frac{(p_A)^{1-\psi}}{(p_A)^{1-\psi} + (p_N)^{1-\psi}} PY, l \in \{R, T\}, \tag{5}$$

where PY denotes the value of the economy's total output. $\frac{(p_A)^{1-\psi}}{(p_A)^{1-\psi}+(p_N)^{1-\psi}}$ denotes the expenditure share on the automatable sector, where p_A is the price index of the automatable sector.[14]

Equation (5) illustrates how the price of tools can affect the adoption of robots. If the price of tools goes up, i.e., Θ_T increases, then firms replace workers and tools with robots, decreasing the total production done with tools. The elasticity of substitution between technologies, θ, is the main parameter governing the magnitude of this effect.

Non-Automatable Sector. In the non-automatable sector, production is carried out one-to-one with an elastically supplied exogenous factor that has a unit price.[15] Therefore,

$$p_N = 1.$$

[13] Artuc et al. (2023), a concurrent work, considers a similar assumption for the productivity of robots.

[14] The price index of the automatable sector is $p_A = \gamma \left(P_R^{-\theta} + \Theta_T^{-\theta}\right)^{-\frac{1}{\theta}}$. γ is the Gamma constant: $\gamma = \left(\Gamma\left(\frac{\theta+1-\sigma}{\theta}\right)\right)^{\frac{1}{1-\sigma}}$.

[15] A similar assumption is made by Acemoglu and Restrepo (2018), with the only difference being that their non-automatable sector produces using labor. As our model takes into account workers with different skill levels, we assume that the non-automatable sector relies on a factor other than labor. This assumption helps us to mitigate the confounding effects of sector labor composition on inequality and enables us to concentrate on the impact of robots and tools. We relax this assumption in the quantitative model in Section 7.

Workers. The labor supply of both types of workers is upward sloping and equals to:

$$\ell_H = A_H w_H^{\xi}$$
$$\ell_L = A_L w_L^{\xi},$$

where A_H and A_L are parameters that affect the levels of labor supply.[16] In Section A.1, we provide the market-clearing conditions and the equilibrium definition.

2.2 Impact of Robots and Tools on Employment

We use the model to study how changes in the prices of robots and tools affect employment and inequality.[17]

The Effect of Robots on Employment is Ambiguous. Proposition 1 summarizes the effect of an exogenous change in the price of robots on the employment of low- and high-skilled workers.

Proposition 1. *The effect of an exogenous increase in the price of robots is ambiguous and given by:*

$$\frac{d\log \ell_L}{d\log P_R} = \beta_R^L \left[(1-s_A)(1-\psi)+\theta\right] \tag{6}$$
$$\frac{d\log \ell_H}{d\log P_R} = \beta_R^H \left[(1-s_A)(1-\psi)+\theta\right], \tag{7}$$

where

$$\beta_R^L = \frac{(\xi+\sigma)\,\xi}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta)+(1-s_{T,H})\delta(\xi+\sigma)\right]+(\xi+\sigma)(1+\xi+(\sigma-1)\delta)} > 0,$$
$$\beta_R^H = \frac{(1+\xi+(\sigma-1)\delta)\xi}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta)+(1-s_{T,H})\delta(\xi+\sigma)\right]+(\xi+\sigma)(1+\xi+(\sigma-1)\delta)} > 0,$$
$$\Delta \equiv 1-\sigma-(1-s_A)(1-\psi)+\left[(1-s_A)(1-\psi)+\theta\right] s_R,$$

[16] For clarity of results, we assume that high- and low-skilled workers have the same labor supply elasticity. This assumption is relaxed in the quantitative model in Section 7.

[17] We leave the proofs to Section A.2.

and $s_{T,H}$ is the income share of high-skilled workers in the tool bundle, s_R is the expenditure share on robots in the automatable sector, and s_A is the economy's expenditure share on the automatable sector.

The effect of robots on employment depends on two counteracting forces: the productivity effect and the displacement effect. The productivity effect is captured by the first term in Equations (6) and (7): $(1 - s_A)(1 - \psi)$. When the price of robots falls, the representative firm in the automatable sector become more productive and expand, increasing the demand for all workers. The displacement effect, given by θ, comes from an increase in the measure of tasks performed by robots, which pushes down the demand for workers when the price of robots decreases. Therefore, the final effect of robots on employment will depend on these two counteracting forces.

Tools Increase Wages and Employment of Low-Skilled Workers. When the price of tools decreases, the demand for low-skilled workers increases, according to Proposition 2 below.

Proposition 2. *The effect of an increase in the price of tools on low-skilled workers is given by*

$$\frac{d\log \ell_L}{d\log P_T} = \beta_T^L \left[(1 - s_A)(1 - \psi)(1 - s_R) - \theta s_R + \frac{s_{T,H}(1-\sigma)(\xi+1)}{s_{T,H}(\sigma-1) + (1 - s_{T,H})(\xi+\sigma)}\right] < 0, \tag{8}$$

where

$$\beta_T^L = \frac{(1-\delta)\xi\left[s_{T,H}(\sigma-1) + (1-s_{T,H})(\xi+\sigma)\right]}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta) + (1-s_{T,H})\delta(\xi+\sigma)\right] + (1+\xi+(\sigma-1)\delta)(\xi+\sigma)} > 0,$$

and Δ is defined in Proposition 1.

When the price of tools falls, there are three forces affecting the demand for low-skilled workers: the productivity effect, the reinstatement effect, and the complementarity effect. All of these forces lead to an increase in the demand for low-skilled workers. The first term in Equation (8), $(1 - s_A)(1 - \psi)(1 - s_R)$, captures the productivity effect. A decrease in the price of tools increases the productivity of the automatable sector, leading to an increase in the demand for workers. The second term in Equation (8), θs_R, is the reinstatement effect. If tools become cheaper, the firm will perform more tasks with workers and tools, increasing the demand for low-skilled workers. The third term in Equation (8), $\frac{s_{T,H}(1-\sigma)(\xi+1)}{s_{T,H}(\sigma-1)+(1-s_{T,H})(\xi+\sigma)}$, comes from the complementarity between tools and low-skilled workers. If tools become cheaper, for the tasks already performed with tools, firms will use more low-skilled workers with tools instead of high-skilled workers, which once again increases the demand for low-skilled workers. Therefore, a decrease in the price of tools increases the employment of low-skilled workers.

The Effect of Tools on High-Skilled Workers is Ambiguous. The effect of an exogenous increase in the price of tools on high-skilled employment is uncertain because it depends on a third force: the substitution effect. When the price of tools goes down, firms have the incentive to shift their production toward tools and low-skilled workers, thereby reducing the demand for high-skilled workers. This intuition is formalized in Proposition 3 below.

Proposition 3. *The effect of an increase in the price of tools on high-skilled workers is given by*

$$\frac{d\log \ell_H}{d\log P_T} = \beta_T^H \left[(1-s_A)(1-\psi)(1-s_R) - \theta s_R + (\sigma-1)\right], \tag{9}$$

where

$$\beta_T^H = \frac{(1-s_{T,H})(1+\xi)(1-\delta)\xi}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta)+(1-s_{T,H})\delta(\xi+\sigma)\right]+(\xi+\sigma)(1+\xi+(\sigma-1)\delta)} > 0,$$

and Δ is defined in Proposition 1.

The terms in Equation (9) capture the productivity, reinstatement, and substitution effects, respectively. The first term, $(1-s_A)(1-\psi)(1-s_R)$, captures the productivity effect: If tools become cheaper, the automatable sector expands, driving up the demand for high-skilled workers. The second term, θs_R, is the reinstatement effect, i.e., if tools become cheaper, firms are going to reinstate workers in tasks previously done by robots. Finally, the last term is the substitution effect, $(\sigma-1)$. If the price of tools decrease, firms will use more low-skilled workers with tools for each task done by labor. This last force reduces the demand for high-skilled workers. Therefore, the final effect of a reduction in the price of tools on labor is ambiguous.[18]

Robots Increase Inequality and Tools Decrease it. A change in the price of machines affects inequality because high- and low-skilled workers have different relationships to tools. When the price of robots goes down, the demand for both worker types changes. If the replacement effect dominates the productivity effect, the demand for both worker types will go down. As an exercise, suppose that the wages of low- and high-skilled workers fell by the same amount. In that case, the low-skilled worker and tool bundle would be relatively more expensive because low-skilled workers are complements to tools, whose price is fixed. Because of the complementarity with tools, the wages of low-skilled workers have to fall by more than the wages of high-skilled workers, which increases inequality. This intuition is summarized in Proposition 4 below.

Proposition 4. *Suppose* $(1-s_A)(1-\psi)+\theta > 0$*, a reduction (increase) in the price of robots increases (decreases) the skill premium,* w_H/w_L*:*

$$\frac{dw_H/w_L}{dP_R} < 0.$$

Tools have the opposite effect on inequality. When the price of tools goes down, the relative demand for low-skilled workers increases because they are complements to tools. As a consequence, the skill premium goes down.

Proposition 5. *A reduction (increase) in the price of tools decreases (increases) the skill premium,* w_H/w_L*:*

$$\frac{dw_H/w_L}{dP_T} > 0.$$

[18]This result shows the importance of production function 4. Suppose that, rather than high- and low-skilled workers being combined to produce a task, they instead performed different tasks. If low-skill workers have more of their tasks exposed to automation, then a decrease in the price of robots increases employment of high-skill workers due to the scale effect. This result is at odds with the empirical findings.

Discussion. The model shows that robots and tools have different implications for employment and inequality. While robots might decrease employment and increase inequality, tools increase employment and decrease inequality. In the following sections, we test these predictions on the data. We identify the particular machines that are the most similar to the model's definition of robots and tools. Then, using data for Brazil, we study their effect on the labor market.

3 Data

In this section, we describe the steps to create a dataset with labor market outcomes and machine imports by sector, region, and year in Brazil. For each sector in a given region, we observe its imports of machinery at the 4-digit HS code level.[19] In the next section, following the insights of the model, we classify these machines as robots or as tools.

RAIS. The main source of labor force information is the administrative dataset RAIS - *Relação Anual de Informações Sociais.* RAIS is a matched employer–employee dataset collected by the Brazilian Ministry of Labor. It covers the universe of formal firms. Its use has been widespread in different areas of economics in recent years.[20]

RAIS contains data on employment, worker demographics, and firm characteristics. For employment, we observe wages, hours of work, date of hiring/firing, the establishment of work, and occupation. We also observe workers' demographics: age, gender, education, and race. Firms' sector and establishment locations are also observed. We use RAIS data from 1997 to 2014.

Imports. We observe monthly imports at the municipality level with data from the Secretary of International Trade. The data contain all imports between 1997 and 2014, with information on year, HS code of the imported product, product name with a detailed description of its characteristics, city of the importing establishment, quantity, and value.

[19] These data were also used by de Souza (2020). Rodrigo (2022) uses robot imports at the regional level from the same source.

[20] de Souza (2020), Dix-Carneiro and Kovak (2019), Dix-Carneiro and Kovak (2017), Colonnelli and Prem (2019) and Colonnelli et al. (2020) are just some examples.

The Secretary of International Trade also records the sector of the importing firm.[21] This administrative dataset records imports by product and sector of the importing firm. This enables us to identify the sector in which each machine is used in without having to rely on input–output tables. [22]

Tariff We use changes in tariffs as exogenous variation to the price of machines. Tariff data come from the World Bank Trade Analysis Information System.

4 Machine Classification

In the data, there are 535 different capital goods imported by manufacturing firms.[23] However, the literature studying automation typically narrows the sample to a specific capital good: industrial robots. This choice reduces the error of misclassifying machine types but greatly limits the scope of the analysis: Industrial robots corresponded to only 3% of all capital imports in Brazil in 2019.

To solve this issue, we propose a text-based method to identify the relationship of machines to labor. We classify machines according to their text similarity to the description of robots and tools, inspired by Argente et al. (2020). The procedure has three steps. First, we use the harmonized system code to get a description of machines imported by Brazilian firms. Second, we select a set of texts that describe robots or tools. Third, we calculate the texts similarity between these texts and the machines being imported. Fourth, we classify each machine as a robot or as a tool, depending on which text the machine is most similar to. We describe the procedure in detail below.

List of Machines. We construct a list of machines imported by Brazilian firms using the description of 6-digits Harmonized System (HS) codes. HS codes are used globally for tax and legal purposes. Therefore, the language used in their description are precise to avoid

[21]To guarantee the anonymity of the firms involved, this dataset is not public.

[22]Products in this dataset are at the 8-digit Brazilian classification. They have the first 6 digits of the international HS plus 2 extra digits, which are specific to Mercorsur.

[23]535 is the number of different capital goods at the Harmonized System 6 digits level.

misclassification and legal disputes. We follow two steps to construct a list of machines adopted by Brazilian firms.

First, we limit the sample of HS products to capital goods that have been imported at least once by firms in a tradable sector.[24] This selection excludes from the list intermediate goods, computers, and office equipment.

Second, we remove from the list HS codes of durable intermediate inputs. To do so, we limit the sample to HS codes from 82 to 90, which cover hand tools, metal items, mechanical appliances, and precision instruments.[25]

The final list contains a detail description of 406 industrial machines imported by Brazilian firms, such as industrial robots or hydraulic presses, and does not contain office equipment, such as computers or printers, or durable intermediate inputs. Table B.1 provides a summarized list of these machines.

Reference Text. Following Argente et al. (2020), we use Wikipedia pages on different machines as descriptions of robots and tools. Each Wikipedia article describes the machine, its main application, and connects it to a broader category. Each Wikipedia category, such as automation or power tools, links different articles under the same theme. We use all Wikipedia articles under the industrial robots category as robot descriptions, while for tools, we use Wikipedia articles under the power tools, hand tools, and cutting tools categories, which describe machines that complement workers in their tasks. In Appendix B.1.1, we provide a complete list of Wikipedia articles used.

Text Similarity. After removing stop-words and lemmatizing the documents, we calculate the cosine text similarity between each machine description and the Wikipedia articles. The algorithm transforms each document into a vector. Each entry in the vector represents a word. If the document contains that word, the entry in the vector is equal to 1 and zero otherwise. The similarity between two documents is given by the cosine distance between

[24]The list of HS products classified as capital goods is from the Secretary of International Trade.

[25]We also remove boilers (8402, 8402), furnace (8416), cooling equipment (8418), office machines (8472), mold bases (8480), lightning equipment (8513, 8516, 8517, 8519), video equipment (8521, 8525, 8526, 8527), display equipment (8528, 8531), lamps (8537, 8539), rafts (8907), medical instruments (9018, 9019, 9020, 9021, 9022), and measuring devices (9023, 9028).

the two vectors. A formal description of the method and weights used is given in Appendix B.1.2, which follows Argente et al. (2020) closely.

Classification. We classify machines as robots or as tools according to its closest Wikipedia article.[26] Let s_{jw} be the text similarity between machine j and Wikipedia article w. The closest Wikipedia article to j is $w_j^* = \arg\max_w s_{jw}$. We call j a robot if w_j^* is a Wikipedia article associated with automation. We call it a tool otherwise.

4.1 Summary Statistics of Robot and Tool Imports

There are three relevant facts that, together, highlight the importance of tools among firms in Brazil.

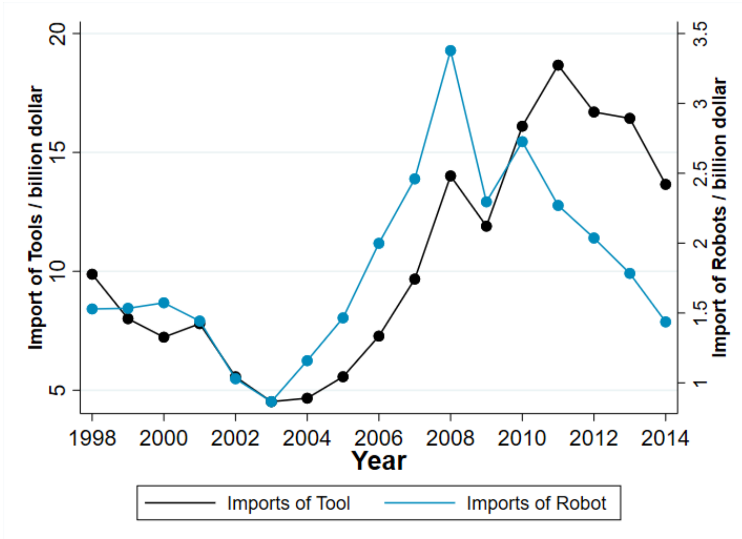
Imports of tools are 10 times larger than imports of robots. Figure 1 shows the statistics for robot and tool imports in Brazil. Figure 1 shows that imports of tools are 10 times larger than those of robots, with both being strongly correlated over time. The high degree of correlation between these two capital types shows the necessity of two instruments to separate the effect of one from that of the other.

Robot adoption is concentrated in a few sectors, whereas tools are common in all sectors. Figure 2 shows the distribution of robot and tool imports across sectors. Tools are common in most sectors, whereas robots are concentrated in the production of transportation and electrical equipment.

Robots and tools have become cheaper over time. Figure 3 shows the average price of robots and tools over time. Since 1998, their prices have decreased by 49% and 42%, respectively, which explains the large increase in the adoption of robots and tools.

[26]It is reasonable to think that some machines do not fall into the category of robot or tool. To deal with that, on the robustness section, we only keep on the classification the machines with highest text similarity to robots or tools.

Figure 1: Robot and Tool Adoption over Time



Description: This figure shows the total imports of HS capital classified as robots or tools in real 2010 dollars.

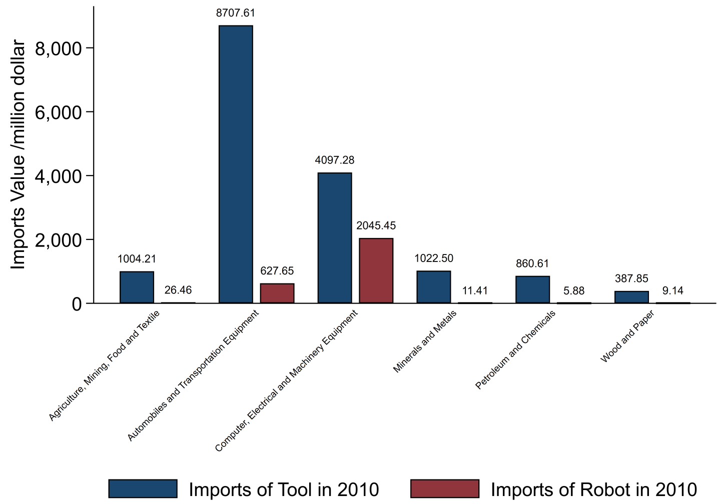
4.2 Validation of Machine Classification

We validate the text-driven machine classification through an extensive number of exercises. First, the classification delivers intuitive results. The machines most associated with robots are "Industrial Robots" and other numerically controlled machines. The ones most associated with tools are an assortment of hand-operated pieces of equipment. Second, the words relevant to the classification algorithm are those directly associated with robots, such as "automatic," "robotic," "control," and "numerical," or those associated with the use of tools, such as "tool," "operate," "handle," and "hand." Third, when machines have words associated with robots, such as "automatic," it strongly increases the probability of them being classified as such. When machines have words associated with tools, such as "tool" or "operate," it increases the probability of them being classified as a tool. Finally, firms adopting machines classified as robots do not change employment, which is similar to what Koch et al. (2021) found when studying industrial robot adoption on the firm level.

Relevant Machines. If a machine is highly associated with the description of robots or tools, it should be easy for the human eye to make this inference. This is why in Table 1 we show the top 5 machines with the highest similarity to tools or robots.

The machines most associated with robots are "Industrial robots", numerically controlled

Figure 2: Robot and Tool Adoption by Sector



Description: This figure shows the imports of robots and tools in 2010 by large sectors.

machines, and those that lift or move objects, such as traveling cranes. This result aligns with previous literature studying automation. Boustan et al. (2022) found that numerically controlled machines replace less educated workers performing routine tasks, just as industrial robots do. Acemoglu and Restrepo (2019) argue that numerically controlled machines, as much as industrial robots, are part of the automation process replacing tasks done by workers. As for machines that lift and move objects, Adachi (2022) notes that some industrial robots specialize in tasks such as "picking alignment, packaging, and material handling," which are also carried out by overhead cranes and other lifting machinery.

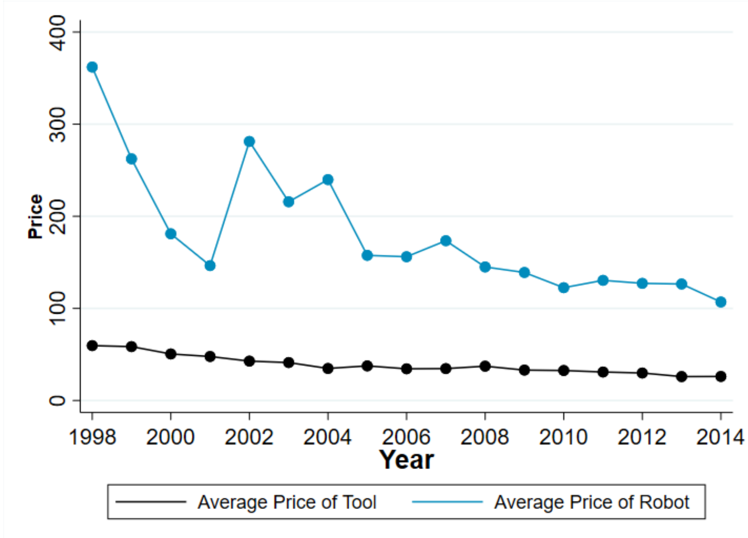
Panel B of Table 1 shows the top 5 machines with the highest similarity to tools. Most of these are hand-operated and used to work with wood or metal.[27]

Words Driving Classification. What words distinguish robots from tools? Are they associated with the nature of automation or equipment handling? Perhaps the algorithm uses counter-intuitive words to classify machines.[28] In this subsection, we show that the key words used to classify machines are related to automation or the handling of equipment.

[27]A thread rolling machine is a machine tool that performs threading in metal. It is commonly used in the production of bolts, nuts, and screws. It usually requires at least one operator per machine.

[28]For instance, if some Wikipedia articles describe an industrial robot as being "electric machines made of steel", the algorithm could use "electric" or "steel" to distinguish robots from tools. If that is the case, we should consider the method a failure because these words do not seem to be associated with the nature of automation.

Figure 3: Average Price of Robots and Tools over Time



Description: This figure shows the average price of robots and tools over time. The price is calculated by dividing total imports by total weight.

Figure 4a shows the distribution of words among machines classified as tools. The most common words are either a synonymous of tool, i.e., "tool," "instrument," or "apparatus,"; an action performed by workers, i.e., "work," or the word "hand." Words common on the description of HS machines, such as "part" or "incl", also appear among tools. Figure 4b shows the most common words among robots. Some of these words, such as "process," "automatic," and "control," are directly associated with automation. Other words, such as "unit," "datum," and "industrial," appear often among robot machines because they are always followed by "automatic" or "numerical control."[29]

Figure 5 shows the importance of words associated with robots or tools to the classification algorithm. We calculate this in two steps. First, we select a set of words associated with tools and a set of words associated with robots. For robots, we pick the words "automatic," "numeric," "control," "robot" and "program". For tools, we use "tool", "hand", "use", "handle", and "instrument". Then, we remove each set of words from the vocabulary, run the algorithm to classify machines, and calculate the correlation between the classification with the full vocabulary and the one without the selected words. In Figure 5, we plot 1 minus

[29]For instance, HS code 844331 "Machines which perform two or more of the functions of printing, copying or facsimile transmission, capable of connecting to an automatic data processing machine or to a network" and HS code 847149 "Data-processing machines, automatic, presented in the form of systems comprising at least a central processing unit, one input unit and one output unit (excl. portable weighing <= 10 kg and excl. peripheral units)". The lemmatization transforms all appearances of "data" to "datum".

Table 1: Machines with Highest Association with Robots and Tools

Rank	Product Code	Description
Panel A. Robots		
1	847950	Industrial robots
2	842611	Overhead travelling cranes on fixed support
3	846021	Grinding machines, for working metal, in which the positioning in any one axis can be set up to an accuracy of at least 0.01 mm, numerically controlled
4	845811	Horizontal lathes, incl. turning centres, for removing metal, numerically controlled
5	842890	Machinery for lifting, handling, loading or unloading
Panel B. Tools		
1	846320	Thread rolling machines, for working metal
2	820530	Planes, chisels, gouges and similar cutting tools for working wood
3	820510	Hand-operated drilling, threading or tapping hand tools
4	820411	Hand-operated spanners and wrenches, incl. torque meter wrenches, of base metal, non-adjustable
5	820412	Hand-operated spanners and wrenches, incl. torque meter wrenches, of base metal, adjustable

Description: Panel A shows the top 5 HS product codes with highest similarity to robots. Panel B shows the top 5 HS product codes with highest similarity to tools. Column 1 shows their ranking, column 2 their HS product code and column 3 their shortened description.

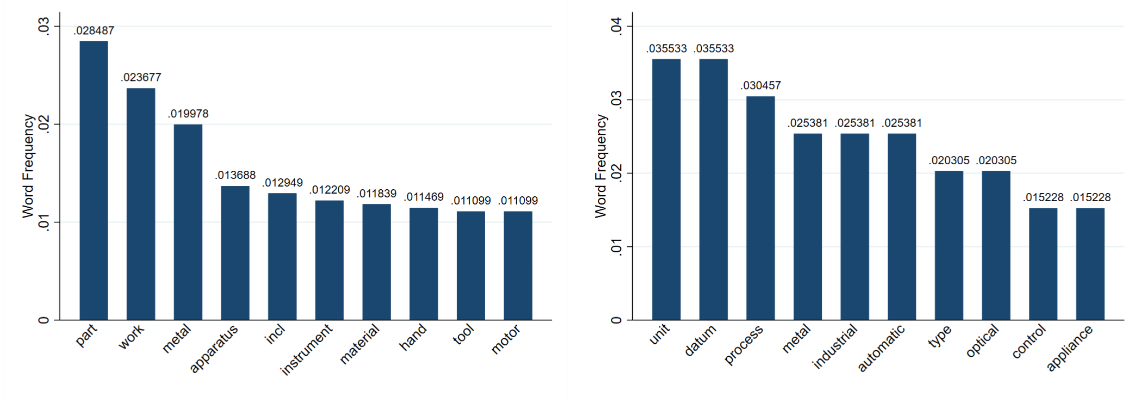
the correlation. If this number is high, it means that removing that word generates a very different classification, which has a weak correlation with the previous one. If it is small, the word removed from the vocabulary does not play an important role. As a reference point, we randomly draw 5 words from the vocabulary 30 times and average the final correlation.

According to Figure 5, words intuitively associated with automation or the handling of equipment are key for the classification algorithm. Figure 5a shows that, as expected, words associated with robots and tools are relevant to the machine classification. Figure 5b shows that the words “automatic”, “control”, and “instrument” are the most important for the machine classification.

Table B.2 in the Appendix shows the effect of different words on the probability that a machine is classified as a robot. Words associated with automation have a strong effect on the probability of a machine being classified as a robot. Words associated with tools, such as “hand” and “instrument,” have a negative but non-significant effect on the probability of a machine being classified as a robot.

Figure 4: Distribution of Words Among Machines Classified as Robots or Tools

(a) Common Words Among Tools (b) Common Words Among Robots



Description: These figures display the distribution of the most common words among HS 6-digit products classified as tools or as robots.

Firm-Level Event Studies. In Section B.1.4, following Koch et al. (2021), we implement a matched difference-in-differences to understand the correlation of machine adoption with employment at the firm level. We find that the adoption of robots does not correlate with firm-level employment, as Koch et al. (2021) found when studying industrial robots. This result suggests that the machines classified as robots affect employment similarly to the industrial robots.

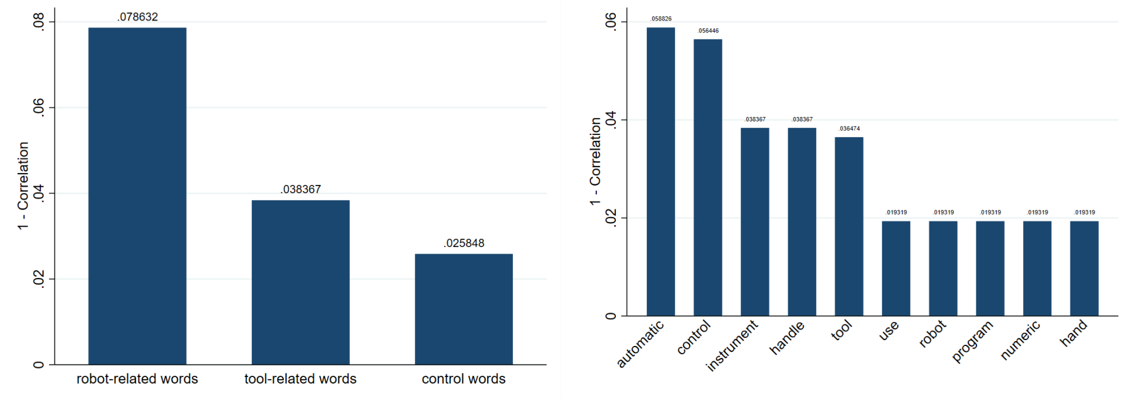
5 Empirics

In this section, we explain how we identify the impact of robots and tools on local labor markets. We do this by comparing employment growth in markets with different levels of exposure to a decrease in tariffs on robots or tools. By studying how machine adoption affects the market as a whole, we capture the broader impact of robots, not just on the firms that adopt them.

Figure 5: Importance of Different Words to the Machine Classification

(a) Importance of Group of Words

(b) Importance of Selected Words



Description: These figures show the importance of different words to the classification algorithm. To calculate this, we first select a set of words related to robots and a set of words related to tools. Robot words are "automatic," "numeric," "control," "robot," and "program". Tool words are "tool," "hand," "use," "handle," and "instrument". Then, we remove words associated with robot or tools from the vocabulary and run the classification algorithm. The figures plot 1 minus the correlation between the classification without a selection of words and the baseline classification. The larger the value of 1 minus the correlation, the more important that group of words is to the final classification. As a comparison group, we randomly select 5 words from the vocabulary 30 times and plot their correlation under "control words". Figure 5b repeats this exercise for each robot- and tool-related word.

5.1 Second Stage

Our main specification is

$$\Delta \log(y_{r,s,t}) = \theta^R \Delta \log\left(robots_{r,s,t}\right) + \theta^T \Delta \log\left(tools_{r,s,t}\right) + X'_{r,s,t}\Theta + \mu_r + \mu_s + \mu_t + \epsilon_{r,s,t}. \tag{10}$$

The left-hand side, $\Delta \log(y_{r,s,t}) = \log(y_{r,s,t}) - \log(y_{r,s,t-5})$, is the 5-year difference in the log of labor market outcome $y_{r,s,t}$ of region r, sector s at year t. $robots_{r,s,t}$ is 1 plus the imports in dollars of robots in the past 5 years. Therefore, $\Delta \log\left(robots_{r,s,t}\right)$ is the growth rate in the imports of robots by region r, sector s at year t.[30,31] Equivalently, $\log\left(tools_{r,s,t}\right)$ is approximately the growth rate in the imports of tools. $X_{r,s,t}$ is a set of controls.[32] μ_r and μ_s are region and sector fixed effects, respectively. Because the model is already in difference,

[30]Sector s corresponds to a 4-digit CNAE2 code. We focus on agriculture, mining, and manufacturing sectors because they are the ones that adopt and implement machines. The sample contain 199 different 4-digit CNAE2 codes.

[31]Each region r is a microregion, similar to a commuting zone in the US. A microregion is made up of municipalities that are economically connected. The Brazilian Institute of Geography and Statistics defines the composition of each microregion. There are 558 microregions in the sample.

[32]The controls are the growth rate of variable $y_{r,s,t}$ in the pre-period, which captures potential labor market trends, the tariff change on sectoral output, the tariff change on inputs excluding capital, the routine task content, and the manual task content, which are defined below.

these fixed effects capture potential differential trends between regions and sectors. μ_t is a time fixed effect.

We use a long-difference model because machine investments are lumpy and labor takes time to adjust. Capital goods are durable; firms do not purchase them repeatedly. Therefore, the estimates in a year-by-year regression would have large variance due to spikes in capital investments. In addition, machine investments should slowly affect the labor market. To account for these two facts, we use a long-difference model.

The parameters θ^R and θ^T measure the impact of robots and tools on the labor market of sector s and region r. First, unlike in Acemoglu and Restrepo (2020), we have sector-region level data on machine adoption. This approach lets us explore the significant variation in machine adoption across markets, as discussed in Section 4.1, to identify the effects of robots and tools. Second, θ^R and θ^T capture the wider effects of robots, not just their direct impact on firms that adopt machines. When firms adopt new machinery, they can lower their prices, which may lead to job losses for their competitors. By taking a market-level approach, our parameters also reflect this employment adjustment.[33]

5.2 First Stage

Machine Imports are Endogenous. To identify the causal effect of robots and tools, we need an instrument. Without exogenous variation, it's impossible to separate the effect of local labor market shocks from the impact of each type of machine. For example, a sectoral preference shock might increase demand in a sector, leading to more capital investment and higher labor demand. Without an instrument, we cannot tell if the tools themselves caused this change or if it was due to the demand shock. Similarly, local labor market shocks can create the same issue. If firms choose to use robots because labor has become more expensive in a region, it's hard to distinguish between the effects of the labor market shock and the robots. Therefore, we construct two instruments to identify the causal effect of robots and tools.

[33]Although studying the effect of machine adoption at the firm level would be interesting, our data do not identify imports at the firm level for a representative sample. In Section B.1.4, we show the effect of robots and tools on a set of firms whose imports we can identify.

Tariffs on Robots and Tools as Instrument. We use tariff changes in machines as an instrument for their adoption. Tariffs meet the two key requirements for instrumental variables: 1) They affect the incentives to buy each type of machine, and 2) They do not affect local labor markets directly, only through cheaper machines. As noted by Dix-Carneiro and Kovak (2017) and Dix-Carneiro and Kovak (2019), Brazil has been opening its economy since the late 1980s. During this period, tariff changes were driven by differences in their starting points, not by current economic shocks.[34] Tariffs affect the after-tax price of machines, encouraging their purchase, but they do not correlate with other economic changes. Below, we show that tariffs are not linked to political connections, other policies implemented during the period, pre-existing labor market trends, or other labor market shocks.

The import tariff on robots of sector s at year t is given by

$$\tau_{s,t}^{R} = \sum_{m} \lambda_{R,m,s} \tau_{m,t} \mathbb{I}\left\{m \ is \ a \ robot\right\} \mathbb{I}\left\{m \ is \ an \ input \ in \ sector \ s\right\} \tag{11}$$

where $\tau_{m,t}$ is the average import tariff on machine m in year t, $\mathbb{I}\left\{m \ is \ a \ robot\right\}$ is a dummy taking one if machine m is classified as a robot, and $\mathbb{I}\left\{m \ is \ an \ input \ in \ sector \ s\right\}$ is a dummy taking one if machine m has ever be imported by firms in sector s, i.e., if it is an input in sector s. $\lambda_{R,m,s}$ is the import share of product m among robots of sector s in 1998. We calculate the tariffs on tools in a similar way.

Following the literature, we exploit heterogeneity on the response to price changes. We explore heterogeneity in the market response to changes in the prices of tools and robots to construct the instrument, following previous work. Autor and Dorn (2013), Graetz and Michaels (2018), and Acemoglu and Restrepo (2020) suggest that robots are more likely to replace workers in routine-intensive jobs. Therefore, markets with more workers in routine-intensive jobs should have higher potential for robot adoption. As a result, these markets should be more responsive to changes in robot tariffs. Based on this idea, we construct the

[34] Figure B.2 in the appendix show that tariffs on robots and tools fell 30% and 27%, respectively, between 1998 and 2014. That decrease comes from a decrease in MFN tariffs and not special trade agreements.

instrument as follows:[35,36]

$$IV^{robots}_{r,s,t} = Routine\ Task\ Content_{r,s,0} \times \tau^{R}_{s,t}, \tag{12}$$

where $Routine\ Task\ Content_{r,s,0}$ is the average routine task content among workers in region r and sector s in 1997.[37] $\tau^{R}_{s,t}$ is the tariff on imports of robots of sector s at time t weighted by pre-period trade flows, as defined in 11.

We create an instrument for the adoption of tools using the same principle. As described in Section 4.2, machines that workers manually operate are more likely to be classified as tools. Therefore, regions with a higher percentage of workers using hand tools are more likely to adopt these tools when their prices decrease.[38] The instrument for tools is given by:

$$IV^{tools}_{r,s,t} = Manual\ Task\ Content_{r,s,0} \times \tau^{T}_{s,t}, \tag{13}$$

where $Manual\ Task\ Content_{r,s,0}$ is the average manual task content among workers in region r and sector s in 1997.[39]$\tau^{T}_{s,t}$ is the tariff on tools.

The first stage is

$$\Delta log(robots_{r,s,t}) = \pi_{1,1}\Delta IV^{robots}_{r,s,t} + \pi_{1,2}\Delta IV^{tools}_{r,s,t} + X'_{r,s,t}\Pi_1 + \mu_r + \mu_s + \mu_t + \epsilon_{r,s,t} \tag{14}$$

$$\Delta log(tools_{r,s,t}) = \pi_{2,1}\Delta IV^{robots}_{r,s,t} + \pi_{2,2}\Delta IV^{tools}_{r,s,t} + X'_{r,s,t}\Pi_2 + \mu_r + \mu_s + \mu_t + \epsilon_{r,s,t}, \tag{15}$$

where $\Delta log(robots_{r,s,t})$ and $\Delta log(tools_{r,s,t})$ are the 5-year difference in robot and tool imports, respectively, as discussed before. $IV^{robots}_{r,s,t}$ and $IV^{tools}_{r,s,t}$ are the instruments for tools and robots. $X_{r,s,t}$ is the same set of controls as before.

[35]A similar approach was used by Graetz and Michaels (2018), Bonfiglioli et al. (2020), and Acemoglu and Restrepo (2022), to name a few.

[36]In the Appendix B.3.2, we use only tariffs as instruments. Results are robust to different instruments.

[37]O*NET provides a dataset measuring the importance of different tasks for each occupation. Through a survey of workers and occupational experts, O*NET measures with a score from 1 to 5 the importance of each task for each occupation. Following the literature, the routine task content is constructed averaging the O*NET questions on the degree of automation and the importance of doing the same task for each occupation.

[38]We thank an anonymous referee for suggesting this instrument.

[39]The manual task content is constructed using all O*NET questions related to the use of hand tools. There is a total of 338 questions relating to the use of different tools. The workers with highest manual task content are blue collar manufacturing workers.

Identifying Variation. The identifying variation in the effect of robots and tools comes from comparing changes in labor market outcomes across markets with varying exposure to tariff changes. For example, Figure B.3 shows a significant decrease in machine tool tariffs in metal ore mining sectors. In contrast, nonmetallic mineral mining saw a smaller decrease. Similarly, as illustrated in Figure B.4b, the region of Manaus, in the North of Brazil, had more manual task occupations compared to the region of Joao Pessoa, in the Northwest. We identify the effect of tools on the labor market by comparing the changes in labor market outcomes between more exposed markets, such as metal ore mining in Manaus, to those less exposed, such as nonmetallic mineral mining in Joao Pessoa, while controlling for tariff changes in robots and trends on these particular markets.

5.3 Validation

A natural identification threat in this setting is the existence of trends and other shocks correlated with the instrument. To validate the identification strategy, we show that the adoption of machines generated by tariff changes is not correlated with political connections to the government, with other policies implemented during the period, with pre-period trends, or with other shocks hitting the Brazilian economy.

Political Connections and Other Policies. If the effect of tariffs on machine adoption were correlated with other policies, we would not be able to separate the effect of machine adoption from the effect of these other policies. Table B.3 in the appendix shows the correlation between the instrument and major policies implemented during the period of analysis. It shows that the instrument is not correlated with subsidized loans, public procurements, or campaign contributions.

Pre-period Trends. If changes in tariffs were correlated with pre-period trends in the labor market, we would not be able to distinguish the effect of tariffs from existing trends in the labor market. Table B.4 shows that the instruments are not correlated with pre-period trends in the labor market.

Other Shocks. The commodity boom happened during our period of analysis. To make sure that our results are not driven by this event, Table B.3 shows that the instruments are not correlated with changes in import prices. There is a weakly statistically - but not economically - significant correlation between the robot instrument and export prices.

6 Empirical Results

In this section, we discuss the effect of robots and tools on the labor market. We first show that our instrument is strongly associated with the adoption of robots and tools. Moreover, while robots have a strong negative effect on employment, tools have an impact with a similar magnitude but in the opposite direction. Therefore, if the adoption of these machines increases by the same amount, the effect on employment will be null. Finally, we show that the effect of robots and tools is concentrated among low-education production workers in occupations directly associated with machine operation.

Significant First Stage with Large Cross-Elasticities. Table 2 displays the instrument's impact on robot and tool adoption. In the baseline specification in columns 2 and 5, an increase in the robot or tool instrument by 1 standard deviation reduces their imports by 23% and 18%, respectively. The F-statistics for all specifications are well above 10, alleviating any concern about weak instruments.[40]

Table 2 also reveals strong cross-elasticities, showing the necessity of considering robots and tools jointly. Raising tariffs on robots reduces the adoption of both robots and tools. Therefore, omitting tools from the main specification, as commonly done in the literature, would not provide the causal effect of robots. Instead, it would identify the effect of robots net of changes in tools.

Robots decrease employment. Table 3 shows the effect of robots and tools on employment. Regardless of the set of controls used, robots cause a strong decline in employment,

[40]Tables B.5 and B.6 show that the instrument is associated with fewer imports in different functional forms. Table B.5 uses the inverse hyperbolic sine to show that an increase in the instrument causes a decrease in the import of robots or tools. Table B.6 shows that the instruments lead to a decrease in the probability of importing at least one tool or robot.

Table 2: First Stage: Effect of Instrument on the Adoption of Robots and Tools

	(1) Δlog $Robots$	(2) Δlog $Robots$	(3) Δlog $Robots$	(4) Δlog $Tools$	(5) Δlog $Tools$	(6) Δlog $Tools$
IV^{tools}	0.0408***	0.0351***	0.0372***	-0.0507***	-0.0634***	-0.0556***
	(0.0047)	(0.0047)	(0.0048)	(0.0076)	(0.0076)	(0.0078)
IV^{robots}	-0.2403***	-0.2424***	-0.2389***	-0.2769***	-0.2800***	-0.2708***
	(0.0125)	(0.0124)	(0.0125)	(0.0125)	(0.0124)	(0.0126)
R^2	0.315	0.338	0.388	0.497	0.523	0.549
F	120.168	119.354	202.091	138.921	143.671	222.011
N	204070	204069	204049	204070	204069	204049
Region FE	–	✓	–	–	✓	–
Sector FE	✓	✓	–	✓	✓	–
Reg-Sec FE	–	–	✓	–	–	✓

Description: This table shows the coefficients of the first stage, i.e., regressions (14) and (15). IV^{tools} is the interaction between the share of non-replaceable occupations and tariffs on tools in each sector. IV^{robots} is the interaction between the share of replaceable occupations and tariffs on robots in each sector. $Robots$ and $Tools$ denote the imports in dollars of robots and tools, respectively, in the past 5-years. The difference is taken over the past 5 years. All specifications have as controls the growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997 and year fixed effects. Columns 1 and 4 add a sector fixed effect, columns 2 and 5 have sector and region fixed effects, and columns 3 and 6 have sector–region fixed effects. Standard errors are clustered at the region–sector level.

which is a result that diverges from previous literature. In the main specification in column 5, a 1% increase in the adoption of robots drives a 0.22% decrease in employment.

Controlling for tools is paramount to identifying the effect of robots. Because decreases in the price of robots also lead to an increase in the adoption of tools, not controlling for tools would lead to an omitted variable bias and mask the true effect of robots. Tables B.7 and B.8 in the appendix show the estimated effect of robots without controlling for tools, instrumenting robots only with the main instrument in (12). The effect of robots in Table B.8 is insignificant and similar in magnitude to other estimates in the literature, such as the ones found by Acemoglu and Restrepo (2020), Dauth et al. (2021), Rodrigo (2022), and Graetz and Michaels (2018), among others. As seen in Table 2, increases in the price of robots are negatively associated with the adoption of tools. Therefore, not controlling for tools results in an upward-biased estimate.[41]

Instrumenting robot adoption with robot imports from other countries while ignoring tools, a prevalent method, once again biases the estimates. Robot imports by other countries correlate with local tool adoption, according to Section B.3.1 of the appendix. Therefore,

[41]Its reasonable to think that not controlling for other inputs, such as materials, could also lead to biased estimates. In Section 6.1, we show that controlling for the imports of other inputs do not change the results.

when tools are not controlled for, one only identifies the effect of robots net of tools. Because we control for the confounding effect of tools, we identify a stronger effect of robot adoption on employment than previously found.

Table 3: Effect of Tools and Robots on Employment

	(1) Δlog *Employment*	(2) Δlog *Employment*	(3) Δlog *Employment*	(4) Δlog *Employment*	(5) Δlog *Employment*	(6) Δlog *Employment*
Δ log(Tools)	0.1502***	0.1545***	0.1496***	0.1826***	0.1738***	0.1942***
	(0.0219)	(0.0224)	(0.0213)	(0.0266)	(0.0245)	(0.0258)
Δ log(Robots)	-0.1105***	-0.1056***	-0.0941***	-0.2333***	-0.2245***	-0.2258***
	(0.0162)	(0.0159)	(0.0142)	(0.0335)	(0.0322)	(0.0330)
N	239581	204070	204069	204070	204069	204049
Region FE	–	–	✓	–	✓	–
Sector FE	–	–	–	✓	✓	–
Reg-Sec FE	–	–	–	–	–	✓

Description: This table shows the coefficients of regression (10) on employment. $\Delta log(Tools)$ and $\Delta log(Robots)$ are instrumented according to equations (12) and (13). *Robots* and *Tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. All specifications include as control year fixed effects. In column 1, there are no controls other than year fixed effects. Column 2 adds the baseline controls, i.e., the growth rate of employment between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, and the average manual task content in 1997. Column 3 adds region fixed effect to the controls. Column 4 adds sector fixed effect to the controls. Column 5 includes as controls the baseline controls, region FE, and sector FE. Column 6 includes sector–region FEs and the baseline controls. Standard errors are clustered at the region–sector level.

Tools increase employment by as much as robots decrease it. Table 3 also shows that tools affect employment: A 1% increase in the adoption of tools leads to a 0.17% increase in employment. Columns 1 to 6 show that the estimate is robust to different specifications, with the elasticity ranging from 0.15 to 0.19.

Tools increase employment at the same rate at which robots decrease it. Therefore, if the adoption of these two machines increases by the same amount, the net effect on employment will not be statistically different from zero.

Robots and tools only affect low-skilled workers who are directly using tools. According to Table 4, robots and tools primarily affect low-skilled workers. A 1% increase in robot adoption decreases the employment and wages of workers with less than a high-school education by 0.22% and 0.04%, respectively. Robots also weakly decrease employment of workers with high-school education and college. As before, tools increase the employment of low-skilled workers by almost as much as robots decrease it.

Table 5 shows that the effect of robots and tools is concentrated among the workers who are directly operating them, i.e., operational or technical workers, and administrative workers, such as HR. The first column shows the effect on managers. Column 2 shows the effect of Tools and Robots on science professionals, which include engineers, chemists, and other STEM college graduates. Column 3 shows the effect of machines on technical workers, i.e., workers in areas associated with STEM but who do not have a college degree. These include those working in mechatronics and chemistry, and electronic technicians, among many others. Despite having technical skills, 62.8% of these workers have not finished high school. Column 4 shows the effect on administrative and office workers. The last column shows the effect of machines on operational workers.

Table 4: Effect of Tools and Robots on Different Educational Groups

	(1) Δlog *H.S. Drop.*	(2) Δlog *Wage H.S. Drop.*	(3) Δlog *H.S. Complete*	(4) Δlog *Wage H.S. Complete*	(5) Δlog *College*	(6) Δlog *Wage College*
Δ log(Tools)	0.1683***	0.0433***	0.0946***	0.0083	0.0468*	0.0209
	(0.0247)	(0.0074)	(0.0274)	(0.0107)	(0.0255)	(0.0130)
Δ log(Robots)	-0.2283***	-0.0482***	-0.0377	-0.0232**	-0.0226	-0.0107
	(0.0324)	(0.0098)	(0.0279)	(0.0110)	(0.0232)	(0.0120)
N	194269	194269	116352	116352	75878	75878
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment of different occupations. $\Delta log(Tools)$ and $\Delta log(Robots)$ are instrumented according to equations (12) and (13). $Robots$ and $Tools$ denote the imports in dollars of robots and tools, respectively, in the past 5 years. The left-hand side in each column is the number of workers in different occupations. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997, year fixed effects, region fixed effects, and sector fixed effects. Columns 1 and 2 show the effect of robots and tools on employment and monthly earnings of workers that have less education than a high-school diploma. Columns 3 and 4 show the effects on workers with high-school diploma. Columns 5 and 6 show the effect on workers with at least some college education. Standard errors are clustered at the region–sector level.

6.1 Robustness

The main empirical results show that robots decrease the employment of low-skilled operational workers, but tools increase it by a similar magnitude. In this section, we show that this conclusion is robust to alternative identification strategies, to the removal of outliers, to the addition of controls, and to limiting the sample to machines with higher text similarity to robots or tools.

Table 5: Effect of Tools and Robots on Different Occupations

	(1) Δlog *Managers*	(2) Δlog *Science Professionals*	(3) Δlog *Technical Workers*	(4) Δlog *Adm Workers*	(5) Δlog *Operational Workers*
Δ log(Tools)	0.0135	0.0116	0.0905***	0.1086***	0.2318***
	(0.0271)	(0.0392)	(0.0302)	(0.0248)	(0.0341)
Δ log(Robots)	0.0140	0.0140	-0.0256	-0.1331***	-0.1936***
	(0.0231)	(0.0321)	(0.0256)	(0.0270)	(0.0386)
N	46422	20288	72857	134132	149619
Region FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment of different occupations. $\Delta log(Tools)$ and $\Delta log(Robots)$ are instrumented according to equations (12) and (13). $Robots$ and $Tools$ denote the imports in dollars of robots and tools, respectively, in the past 5 years. The left-hand side in each column is the number of workers in different occupations. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997, year fixed effects, region fixed effects, and sector fixed effects. In column 1, is the number of managers, i.e., 1-digit CBO 2002 occupations 0 and 1; in column 2 is the number of science professionals, i.e., 1-digit CBO 2002 occupation 2; in column 3 is the number of technical workers, i.e., 1-digit CBO 2002 occupation 3; in column 4 is the number of administrative workers, i.e., 1-digit CBO 2002 occupation 4 and 5; and in column 5 is the number of operational blue collar workers, i.e., 1-digit CBO 2002 occupation 6 and 7. Standard errors are clustered at the region-sector level.

Tariff as Instruments. In Section B.3.2, we reproduce the main regressions but using only using tariff variation as the instrument. We still reach the same conclusion: Robots decrease the employment of low-skilled operational workers, but tools increase it by equal magnitude.

Import by Other Countries as Instruments. In Section B.3.1, inspired by Acemoglu and Restrepo (2020) and Dauth et al. (2021), among others, we use as the instruments the imports of robots and tools by the US and Europe. We still find that tools increase the employment of low-skilled workers, whereas robots decrease it.

Controlling for Other Inputs. Failing to control for tools can bias the estimated effect of robots because robots increase the adoption of tools, which also impacts the labor market. Additionally, robots or tools may lead to the adoption of other inputs. If these inputs directly affect the labor market, not controlling for them would also bias the estimates. In Tables B.26 and B.27, we add imports of materials (products that are neither robots nor tools) as controls in the baseline specification. Despite this, we still find that tools increase employment for low-skilled workers, while robots decrease it.

Outliers. It could be the case that our results are driven by specific outliers in the sample. To assess whether this is the case, in Section B.3.3 of the appendix, we repeat the main regressions but remove the markets in the top and bottom 0.1% and 0.5% change in tariffs. We still reach the same conclusion that robots decrease the employment of low-skilled operational workers, whereas tools increase it.

Controls. In Tables B.21 to B.32, we show that the results are robust to adding or removing controls. We try five different specifications. First, we remove region and sector fixed effects, which capture regional and sectoral trends. Second, we add only a sector fixed effects. Third, we control for joint sector–region fixed effects, which controls for market-specific trends. Forth, concerned with potential shocks to the growth rate of large regions, we control for initial period employment interacted with an year fixed effect. Fifth, concerned with trends on the growth rate of labor outcomes, we add as control pre-period growth rates interacted with year fixed effect. In all these specifications, we still find that low-skilled workers who directly operate machines are more affected by both robots and tools.

Higher Degree of Text Similarity. The text similarity to the description of robots or tools is, most likely, a noise measure of the true nature of the machine. Moreover, it is possible that not all machines fall into these two classifications. To deal with this, Section B.3.5 shows the main results restricting the sample to the set of machines that have cosine text similarity above the median. We still find that robots decrease employment while labor-augmenting tools increase it.

7 Quantitative Model

In the empirical section, we have learned that tools increase employment and decrease inequality. Robots, meanwhile, increase inequality and decrease employment. These results reveal a trade-off between inequality and productivity. Increased robot adoption increases productivity but also leads to higher inequality. A government concerned with redistribution might be interested in either taxing robots, as in Beraja and Zorzi (2022), or subsidizing the adoption of tools. In this section, we develop a quantitative model of robots and tools with capital accumulation, input-output, international trade, and regions to derive counterfactuals on the aggregate effect of robots and tools and to study policy implications.

The main channel in the quantitative model is the choice that firms make between robots, which replace workers, and tools, which complement them. To interpret the empirical elasticity and capture important elements of the economy, we add other features to the model. We extend the production function specified in (3) requiring high-skilled workers to be used with robots. There are multiple regions and sectors, enabling us to reproduce the empirical strategy in the model. Firms are heterogeneous in their productivity to use different technologies and in the productivity of high-skill workers, which leads to selection into technology types. Firms use inputs from other sectors and export their output to other countries; this has been added to the model to better capture the scale effect.[42] The economy has local production and imports of robots and tools. Households choose their sector and region of employment, accumulate capital that is rented to firms, and make educational choices.

7.1 Demographics

There are $n \in \{1, ..., N\}$ regions and $s \in \{1, ..., S\}$ sectors. We denote workers in sector $S+1$ as out of the labor force. There are 6 agents in the economy: intermediate goods producers, composite goods producers, capital producers, capitalists, workers, and the government. Intermediate goods producers produce using high-skilled workers, low-skilled workers, tools, robots, and inputs from other sectors. Composite goods producers create final goods by aggregating local production with imports from all other countries. Capital producers produce tools and robots using final goods and imported capital. Capitalists accumulate capital from capital producers and rents it to firms to maximize their lifetime utility. Workers choose their region and sector of employment. At the beginning of their life, they choose whether to become high-skilled or low-skilled. The government taxes labor, rents, profits, and imports. It also provides social security to workers outside of the labor force.

[42]Input-output connections are a key feature in understanding the effect of robots and tools for two reasons. First, as Figure C.1 in the appendix shows, robot adoption is more common among downstream sectors, while tools are scattered over sectors. Therefore, changes in the price of robots and tools will have different propagation through the economy. Second, input-output connections and international trade are important for understanding the productivity effect, which measures how the adoption of robots and tools affects the market size of firms and sectors.

7.2 Intermediate Goods Producers

Production Function with Input-Output Connections. Firms perform a set of tasks and use inputs from other sectors to produce. Output of firm i in region n and sector s is:

$$y_n^s(i) = \left[\frac{1}{\gamma^s}\left(\int_0^1 [y_n^s(i,\nu)]^{\frac{\lambda-1}{\lambda}} d\nu\right)^{\frac{\lambda}{\lambda-1}}\right]^{\gamma^s} \prod_{s'=1}^{S}\left[\frac{1}{\gamma^{ss'}} M_n^{ss'}(i)\right]^{\gamma^{ss'}}, \tag{16}$$

where, similar to the simple model, $y_n^s(i,\nu)$ denotes the firm's output of task ν. λ is the elasticity of substitution between tasks. $M_n^{ss'}(i)$ denotes the quantity of sector s' composite goods used by the firm. γ^s denotes the value-added share of the firm's gross output and $\gamma^{ss'}$ denotes the input-output shares. Firm production is a constant return to scale: $\gamma^s + \sum_{s'=1}^{S} \gamma^{ss'} = 1$.

Robots or Tools. Task ν can be performed with robots or tools and workers:

$$y_n^s(i,\nu) = y_n^{s,R}(i,\nu) + y_n^{s,T}(i,\nu).$$

If firm i performs task ν with robots, the production function is:

$$y_n^{s,R}(i,\nu) = Z_n^{s,R}(i,\nu)\left(\ell_n^{s,H,R}(i,\nu)\right)^{\eta}\left(K_n^{s,R}(i,\nu)\right)^{1-\eta},$$

where $K_n^{s,R}(i,\nu)$ is robot capital, $Z_n^{s,R}(i,\nu)$ is the productivity of firm i in completing task ν with robots, and $\ell_n^{s,H,R}(i,\nu)$ is the number of high-skilled workers that firm i employs on task ν. η denotes the expenditure share on high-skilled workers if the firm completes the task with robots.

If firm i performs task ν with tools, the task production function is:

$$y_n^{s,T}(i,\nu) = Z_n^{s,T}(i,\nu)\left[A_n^{s,H}(i)\left(\ell_n^{s,H}(i,\nu)\right)^{\frac{\sigma-1}{\sigma}} + \left(\ell_n^{s,L}(i,\nu)^{\delta} K_n^{s,T}(i,\nu)^{1-\delta}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}},$$

where $\ell_n^{s,H}(i,\nu)$ is the number of high-skilled workers, $\ell_n^{s,L}(i,\nu)$ is the number of low-skilled workers, and $K_n^{s,T}(i,\nu)$ is the amount of tool capital. $Z_n^{s,T}(i,\nu)$ is the productivity of tools for firm i in sector s and region n in task ν. $A_n^{s,H}(i)$ is the high-skilled biased productivity of firm i, which captures that some firms are more productive with high-skilled workers.

Firm Heterogeneity. Firms are heterogeneous in the productivity of using robots, $Z_n^{s,R}(i,\nu)$, tools, $Z_n^{s,T}(i,\nu)$, and high-skilled workers, $A_n^{s,H}(i)$. We assume that $Z_n^{s,l}(i,\nu), l \in \{R,T\}$ follows a Fréchet distribution i.i.d. across regions (n), sectors (s), firms (i), tasks (ν), and technologies (l):

$$F_{Z_n^{s,l}(i,\nu)}(z) = \exp\left[-T_n^{s,l}(i) \times z^{-\theta}\right].$$

We normalize $T_n^{s,T}(i) \equiv 1$ and assume that $A_n^{s,H}(i)$ and $T_n^{s,R}(i)$ follow a joint log-normal distribution (see Section C.2). θ is a key parameter governing the substitution between technologies that will be estimated using the empirical results.

7.3 Sectoral Production and Goods Trade

Sectoral Aggregates. Output at the region–sector level combines the output of firms with elasticity of substitution ϕ:

$$y_n^s = A_n^s \left(\int_0^1 \left[y_n^s(i)\right]^{\frac{\phi-1}{\phi}} di \right)^{\frac{\phi}{\phi-1}},$$

where A_n^s denotes region–sector level productivity.

Imports, Regional Trade, and Composite Goods. Region–sector composite goods combine the same sector's output from all domestic regions and abroad with elasticity of substitution ϵ^s, which is also the trade elasticity:[43]

$$Q_n^s = \left[\sum_{n'=1}^{N+1} (y_{nn'}^s)^{\frac{\epsilon^s-1}{\epsilon^s}} \right]^{\frac{\epsilon^s}{\epsilon^s-1}},$$

where $n' = N+1$ indicates the international market. Inter-region trade and importing incur a trade cost, $h_{nn'}^s$, and importers pay tariffs to the Brazilian government at rate τ^s. Denote

[43]These assumptions for sectoral production and trade are standard in the international trade literature. See Caliendo et al. (2019), among others.

$t^s = 1 + \tau^s$, including the foreign price p^s_{N+1} in the importing cost h^s_{nN+1}. Consequently, the composite goods price is:

$$(P^s_n)^{1-\epsilon^s} = \sum_{n'=1}^{N} (p^s_{n'} h^s_{nn'})^{1-\epsilon^s} + (h^s_{nN+1} t^s)^{1-\epsilon^s},$$

where p^s_n is the price of sector s region n sectoral output.

7.4 Capital Goods Sector

In the capital goods sector, there are two types of agents: capital producers and capitalists. Capital goods are produced by the capital producer using domestic final goods and imported capital. Capitalists are responsible for making inter-temporal investment decisions. Capitalists own capital producers and capital. Capital is then rented to firms.[44]

Capital Producers. Every region–sector has a robot and tool producer. Production of these goods combines domestic final goods with imported capital. The production of investment goods has decreasing returns to scale.[45] The problem of a capital producer of good $l \in \{R, T\}$ is:

$$\begin{aligned} \max_{M^{s,l}_n} \Pi^{s,l,P}_n &= P^{s,l}_n I^{s,l}_n - \Sigma^{s,l}_n M^{s,l}_n, \\ \text{s.t. } I^{s,l}_n &= (M^{s,l}_n)^{1-\xi^l},\ \xi^l \in (0,1) \\ \Sigma^l_n &= \left([P_n]^{1-\epsilon^l} + \left[h^{s,l}_{nN+1}(1+\tau^{s,l}) \right]^{1-\epsilon^l} \right)^{\frac{1}{1-\epsilon^l}}, \end{aligned} \tag{17}$$

where $M^{s,l}_n$ is a composite good combining domestic final goods and import of capital l, $\xi^l \in (0,1)$ is the degree of decreasing return to scale, $P^{s,l}_n$ is the price of capital good l, and Σ^l_n is the cost index. Denote $t^{s,l} = 1 + \tau^{s,l}$. ϵ^l denotes the elasticity of substitution between domestic final goods and imported capital goods, which is also the trade elasticity for capital goods.

[44] This setup follows the literature that studies the adjustment cost of capital, for example, Cooper and Haltiwanger (2006).

[45] We add decreasing returns to scale in capital production to ensure that an equilibrium always exists.

Capitalists and Dynamic Problem. Capitalists accumulate capital from capital producers to maximize their lifetime utility. Each region–sector has a capitalist that invests in robot and tool capital. Their problem is given by:

$$\max_{I_{n,t}^{s,l}} \sum_{t=0}^{\infty} \beta^t \log(C_{n,t}^{s,l}), \ l \in \{R, T\} \tag{18}$$
$$\text{s.t. } K_{n,t+1}^{s,l} = (1-\delta)K_{n,t}^{s,l} + I_{n,t}^{s,l}$$
$$P_{n,t}C_{n,t}^{s,l} = (1-B)(R_{n,t}^{s,l}K_{n,t}^{s,l} - P_{n,t}^{s,l}I_{n,t}^{s,l} + \Pi_n^{s,l,P}).$$

$R_{n,t}^{s,l}K_t$ indicates the capitalist's rental income and $\Pi_n^{s,l}$ the profit of capital producers, which is owned by capitalists. Capitalists spend on investment, $P_{n,t}^{s,l}I_t$, and on the consumption of local final goods after paying. They also pay taxes at a rate of B.

7.5 Workers

Demographics, Sectoral, and Regional Choice. There are two types of workers: high-skilled and low-skilled. In each period, workers select their next period's region and sector. Workers can also choose to stay outside the labor market and receive social insurance.

To accommodate adjustments in the supply of skills, we assume that with probability $1-\lambda^H$, a high-skilled worker dies, which is similar for low-skilled workers with probability λ^L. The dead worker is replaced by an entrant in the same region–sector who decides whether to become a high- or low-skilled worker.

Worker's Dynamic Problem. Building on Artuç et al. (2010), Caliendo et al. (2019), and Kleinman et al. (2023), among others, we assume that a worker of type e has the following recursive utility:

$$\mathbb{V}_{n,t}^{s,e} = \log(u_{n,t}^{s,e}) + \max_{n' \in \{1,2,\ldots,N\}, s' \in \{1,\ldots,S,S+1\}} \left\{ \lambda^e \beta \mathbb{E}_t \left(\mathbb{V}_{n',t+1}^{s',e} \right) - \kappa_{n'n,t}^{s's} + \rho^e \epsilon_{n',t}^{s',e} \right\}, e \in \{H, L\},$$

$$\text{where } u_{n,t}^{s,e} = \max_{\left\{C_{n,t}^{ss',e}\right\}} a_{n,t}^{s,e} \prod_{s'=1}^{S} \left(\frac{C_{n,t}^{ss',e}}{\alpha^{s'}} \right)^{\alpha^{s'}} \quad \text{s.t.} \quad \sum_{s'=1}^{S} P_{n,t}^{s'} C_{n,t}^{ss',e} = (1-B) w_{n,t}^{s,e}, \tag{19}$$

where $\mathbb{V}_{n,t}^{s,e}$ is the value function of a worker in region n, sector s, and education e at time t. Workers choose their location next period, n', sector, s', and consumption of sectoral goods, $\left\{C_{n,t}^{ss',e}\right\}$. α^d and $a_{n,t}^{s,e}$ are parameters of the utility function representing the sectoral consumption shares and consumption shifters. $\kappa_{n'n,t}^{s's}$ is the mobility cost from region n, sector s to region n', sector s'. $\epsilon_{n',t}^{s',e}$ is a preference shock for regions and sectors following a Type-I extreme value distribution i.i.d. across regions, sectors, and time.[46] The income of a worker in the outside sector is equal to the social insurance payment: $w_{n,t}^{S+1,e} = b$.

Define $v_{n,t}^{s,e} \equiv E_{\left\{\epsilon_{n',t}^{s',e}\right\}} \mathbb{V}_{n,t}^{s,e}$. Using the extreme value distribution's property, the expected region–sector–type value function equals:

$$v_{n,t}^{s,e} = \log(a_{n,t}^{s,e}) + \log(1-B) + \log\left(\frac{w_{n,t}^{s,e}}{P_{n,t}}\right) + \rho^e \log \sum_{n'=1}^{N} \sum_{s'=1}^{S+1} \exp(\lambda^e \beta v_{n',t+1}^{s',e} - \kappa_{n'n,t}^{s's,e})^{1/\rho^e}. \tag{20}$$

Human Capital Choice. To account for changes in the supply of workers as a consequence of changes in the price of tools and robots, we assume that exits are replaced by entrants who choose their skill type. At the end of period t, ζ^e workers die and are replaced with entrants. These entrants are in the same sector and region as the ones exiting and choose their skill level for the next period. Their problem is given by:

$$\max \left\{ \beta v_{n,t}^{s,H} - f^H + \tilde{\rho} \tilde{\epsilon}_{n,t}^{s,H}, \beta v_{n,t}^{s,L} + \tilde{\rho} \tilde{\epsilon}_{n,t}^{s,L} \right\}, \tag{21}$$

where f^H denotes the fixed cost of becoming high-skilled and $\tilde{\epsilon}_{n,t}^{s,e}$ is a preference shock that is i.i.d. across regions, sectors, time, and skill types.

[46] $F(\epsilon) = \exp(\exp(-\epsilon - \bar{\gamma}))$, where $\bar{\gamma}$ is the Euler constant.

Government. The government taxes workers, capital producers, capitalists, and imports to subsidize social security for workers outside of the labor force. The social insurance payment to a worker not in the labor force is endogenously determined by the government's budget constraint, written as the following:

$$
\begin{aligned}
&(1-B)b\sum_{n=1}^{N}(\ell_n^{S+1,H}+\ell_n^{S+1,L}) = \\
&B\sum_{s=1}^{S}\sum_{n=1}^{N}\left(w_n^{s,H}\ell_n^{s,H}+w_n^{s,L}\ell_n^{s,L}+R_n^R K_n^R-\Sigma_n^R M_n^R+R_n^T K_n^T-\Sigma_n^T M_n^T\right)+TD_n. \qquad (22)
\end{aligned}
$$

The left-hand side refers to the net social security payment to those who do not work (in sector $S+1$). On the right-hand side, tax revenues include social insurance taxes and foreign transfers, TD_n, which are equal to the trade deficit due to trade in composite goods and imported capital goods.[47]

8 Model Estimation

The model is estimated by targeting key moments of the Brazilian economy and the elasticities that we identified in Section 6. In this section, we briefly discuss the estimation strategy. We leave the details to Section C.

Calibration. Sectoral trade elasticities, input-output coefficients, final consumption shares, and the social insurance tax rate are set to the numbers estimated by De Souza and Li (2022). We estimate the migration elasticities for both skill types and the skill choice elasticity exploiting variation in migration shares across regions and sectors, the region-sector specific share of new workers that are high skilled, and cross region–sector differences in real wages, following the method by Artuç et al. (2010), Dix-Carneiro (2014), and Caliendo et al. (2019).[48] Exit rates by skill group are calibrated to match movements out of the labor force

[47]See Equation (C.19).

[48]We follow the literature to instrument current wages with past wages, which are unlikely to correlate with current amenity shocks.

from RAIS. We present the details of calibrating these parameters in Section C.3.[49]

We estimate the trade elasticities for robots and tools by regressing changes in their imports on changes in their tariffs, controlling for region and sector fixed effects. We estimate robot trade elasticity to be 7.81 and tool trade elasticity to be 5.59.[50] We present the details of estimation strategy and estimated values in Section C.3.

Estimation. We estimate the parameters related to production and technology choice to reproduce the identified effect of robots and tools on the labor market. We generate in the model the tariff changes observed between 1997 and 2010 and, employing the same identification strategy, we choose θ, the elasticity of substitution between robots and tools; σ, the elasticity of substitution between high-skilled and low-skilled workers; η, the share of high-skilled workers in output produced with robots; and δ, the share of low-skilled workers in output produced with tools, to reproduce the identified effect of robots and tools on the employment of high- and low-skilled workers. As shown in Propositions 1 and 2, these parameters play a critical role in the effect of robots and tools on the employment of different skill groups. We present the details of the estimation procedure in Section C.4. Table 6 shows the main parameters; the remaining ones are presented in Section C.4.

Table 6: Parameters Estimated in the Model: Robot and Tool Technologies

Parameter	Name	Value
θ	Elasticity of substitution between robots and tools	12.1687
ζ	Elasticity of substitution between high- and low-skilled workers in tool technology	2.0098
η^H	Share of high-skilled workers in output produced with robots	0.0918
δ^L	Share of low-skilled workers in output produced with tools	0.5524

Description: This table presents the model parameters that are estimated with the SMM method in the model and focuses on the important parameters related to robot and tool technologies. We present the other estimated parameters in Table C.5.

9 Quantitative Results

If the Prices of Machines Fall by the Same Amount, Employment Does Not Significantly Change. Figure 6 shows the aggregate effect of changes in the prices of

[49]The migration elasticity refers to the elasticity of migration flow to current real wage. The skill choice elasticity refers to the elasticity of high-skilled worker share in region-sector new employment with respect to the difference between high-skilled and low-skilled value functions. We follow the literature to instrument current wages with past wages, which are unlikely to correlate with current amenity shocks.

[50]These estimates are similar to what Parro (2013) obtained for overall capital goods.

robots and tools.[51] Each plot contains changes in the prices of robots and tools on the x-axis. On the y-axis, the figures display aggregate employment, GDP, welfare, and skill premium in the Brazilian economy. Unlike the empirics, which only identify relative effects, the model uncovers the aggregate consequences of changes in the prices of robots and tools.

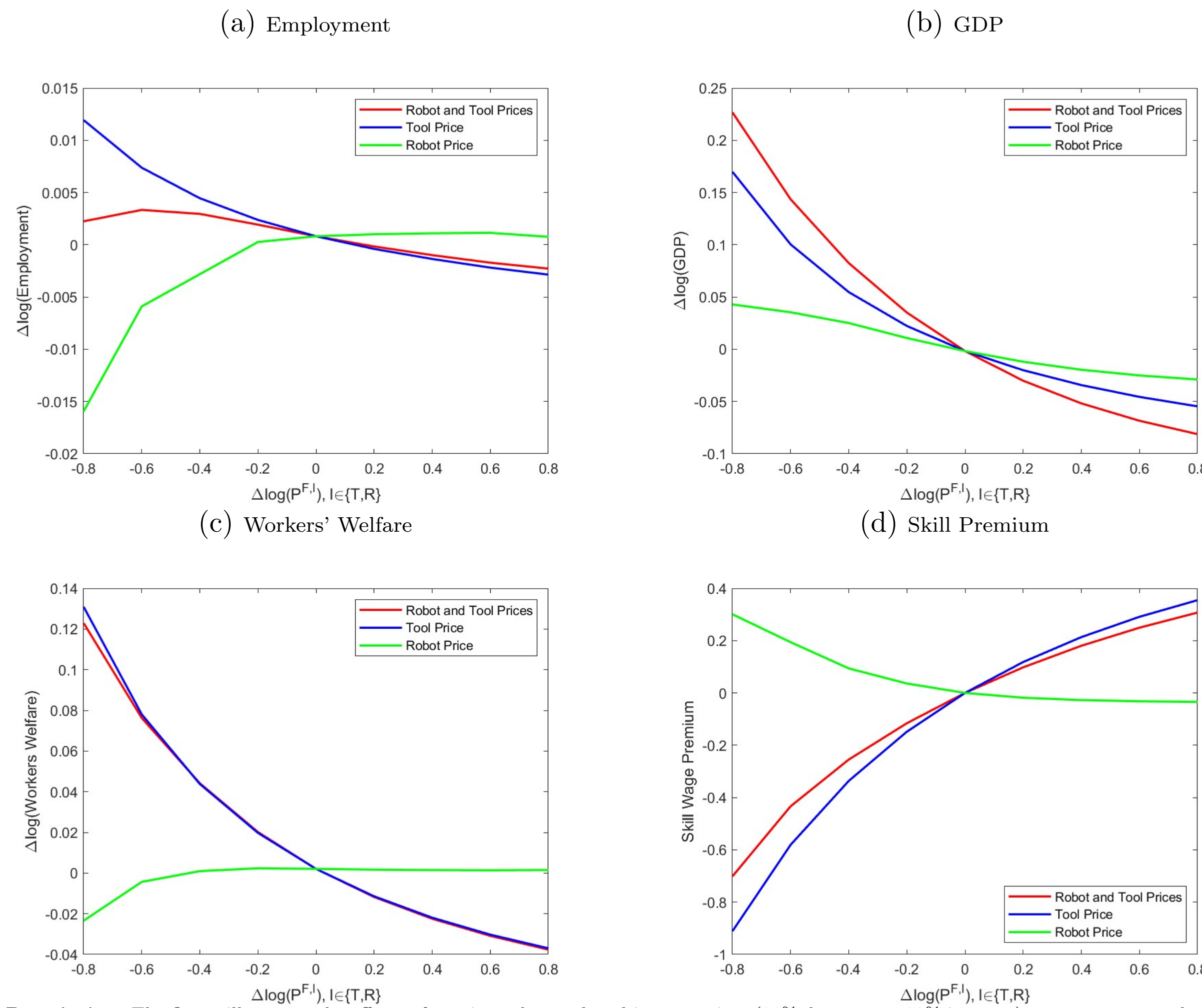
Figure 6 shows that a decrease in the price of robots would decrease employment and welfare while increasing GDP and skill premium. A 80% drop in the price of robots would decrease employment by 1.5%. While robots do complement high-skilled workers, the proportion of high-skilled workers involved in robot technology is relatively low. Therefore, the substitution effect dominates and robots decrease employment. Because low-skilled workers are being replaced by robots, their welfare decreases. GDP increases from lower robot prices because firms become more productive with less expensive capital. Skill premium increases because robots lead to more layoffs of low-skilled workers.

According to the results in Figure 6, if the prices of robots and tools fell by the same amount, welfare would increase and inequality would decrease without a significant effect on employment. The red line in Figure 6 plots changes in employment, GDP, workers' welfare, and skill premium from same price changes to both machines. Tools and robots have an opposite effect on the labor market. Robots replace low-skilled workers in their tasks, whereas tools reinstate them. Because these effects are of comparable magnitude, aggregate employment barely changes if the prices of these two machines fall by the same amount. GDP and welfare, meanwhile, increase significantly from the reduced machine cost. If the price of machines decreases, firms reduce their marginal cost, which benefits consumers. Inequality decreases because tools are complements to low-skilled workers.

Cheaper Robots and Tools Increased Welfare and Decreased Inequality. Between 1997 and 2014, the after-tariff import price of robots and tools fell by 49.4% and 42.3%, respectively. How has that affected the Brazilian economy? Table 7 displays the effects of reduced capital goods prices on the Brazilian economy. The first line shows the counterfactual with both capital prices changing. On the second line, only the tool price changes, and on the third line, only the robot price changes.

[51]We present formulas that compute these aggregate statistics in Section C.6.

Figure 6: **Aggregate Effects of Robot and Tool Capital Import Price Changes**



Description: The figure illustrates the effects of varying robot and tool import prices (80% decrease to 80% increase) on aggregate employment, GDP, workers' welfare, and skill premium, relative to the initial steady state. Red lines represent simultaneous robot and tool price changes, blue lines represents tool-only changes, and green lines represents robot-only changes. Uniform price changes across all sectors are considered.

Cheaper robots and tools, due to advances in the production of these technologies, has led to large GDP gains in Brazil with small changes in employment and lower inequality. Due to cheaper tools, employment has increased. Because both machines have led to higher productivity, GDP and welfare has increased. Moreover, because tools are compliments to low-skilled workers, inequality in the labor market has decreased.

Table 7: Aggregate Effects of Reduced International Capital Goods Prices

	Avg. Robot Price Chg.	Avg. Tool Price Chg.	Employment	GDP	Workers' Welfare	Skill Premium
Both Robots and Tools	-49.4%	-42.3%	-0.1%	7.4%	3.5%	-6.2%
Tools	0	-42.3%	0.9%	5.1%	4.1%	-10.0%
Robots	-49.4%	0	-0.5%	1.6%	-3.9%	4.7%

Description: This table presents the initial trade flow weighted average of international robot and tool price changes, and the effects of lower international capital goods prices on employment, GDP, workers' welfare, and skill premium. The skill premium is defined as the average wage of a high-skilled worker relative to the average wage of a low-skilled worker.

Taxing Robots Increases Welfare. Robots and tools introduce a trade-off between productivity and redistribution. Robots increase productivity while tools reduce inequality. Table 8 highlights this trade-off. It shows the optimal budget neutral tariffs on robots and tools to maximize different objectives of the government.[52]

If the government wants to maximize production, it should subsidize robots. Because the international price of robots is higher, the marginal productivity of robots is higher than the marginal productivity of tools. Therefore, when the government subsidizes robots relative to tools, output goes up. The second line of Table 8 shows the optimal policy when the government wants to minimize labor market inequality. In this case the government should subsidize tools because it increases the relative demand for low-skill workers.

To maximize welfare, the government should tax robots and subsidize tools. On the one hand, subsidizing robots increases production, which benefits workers by increasing overall consumption. On the other hand, tools increase the demand for low-skill workers, transferring income to workers with higher marginal utility. According to Table 8, the redistribution effect is stronger and the optimal policy is to weakly discourage the adoption of robots.

Table 8: Optimal Tariffs/Subsidies on Robots and Tools

Tariffs/Import Subsidies that Maximize	Employment	GDP	Workers' Welfare	Skill Wage Premium	Avg. Robot Tariff/Subsidy	Avg. Tool Tariff/Subsidy
GDP	1.6%	1.8%	-0.2%	7.6%	-8.9%	0.3%
- Skill Wage Premium	0.1%	0.5%	1.1%	-4.8%	28.8%	-5.6%
Welfare	0.0%	0.7%	1.4%	-2.9%	2.6%	-0.7%

Description: This table presents the change in employment, GDP, worker's welfare, and skill wage premium from different tariffs in robots and tools. Tariffs are set on the imports of robots and tools to maximize GDP, Welfare, or to minimize the skill wage premium. Appendix C.9 lays out the problem of the government. The first line shows the effect of tariffs that maximize GDP, the second line shows the effect of tariffs that minimize inequality, the last line shows the effect of tariffs that maximize worker's welfare.

10 Conclusion

Technological progress over the past few decades has led to cheaper robots and tools. In this paper, we shed light on how this phenomenon has affected the labor market in Brazil. We find that while the adoption of robots has led to substantial declines in the employment

[52]We present the government's optimal tariff problem in Section C.9. The government optimally sets import tariffs/subsidies on robots and tools to achieve one of the three policy objectives: maximizing (1) GDP, (2) welfare, and (3) minimizing the skill wage premium (inequality). To ensure that we find an interior solution, we require that the government maintains a balanced budget for these subsidies and tariffs: The tariffs collected from robot and tool imports cannot exceed the subsidies paid for them.

and wages of low-skilled workers in operational occupations, the simultaneous decrease in the cost of tools has played a vital role in mitigating these job losses.

We used natural language processing and an instrumental variable approach to overcome the challenges associated with classifying machines and finding their causal effect. With natural language processing, we identified machines related to automation and those that complement workers in their tasks. We used import tariff variation as an instrument for the adoption of robots and tools.

Our research makes significant contributions to the existing literature on the effect of automation on the labor market. Notably, we expand the analytical framework by adding tools. Additionally, our findings challenge previous estimations of the impact of robots on employment, emphasizing the importance of accounting for the simultaneous adoption of tools, which has often been overlooked in previous analyses.

References

Acemoglu, D., C. Lelarge, and P. Restrepo (2020): "Competing with Robots: Firm-Level Evidence from France," *AEA Papers and Proceedings*, 110, 383–88.

Acemoglu, D. and P. Restrepo (2018): "Modeling Automation," *AEA Papers and Proceedings*, 108, 48–53.

——— (2019): "Automation and New Tasks: How Technology Displaces and Reinstates Labor," *Journal of Economic Perspectives*, 33, 3–30.

——— (2020): "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 128.

——— (2022): "Tasks, Automation, and the Rise in U.S. Wage Inequality," *Econometrica*, 90, 1973–2016.

Adachi, D. (2022): "Robots and Wage Polarization:The Effects of Robot Capital by Occupations," *Working Paper*.

Adachi, D., D. Kawaguchi, and Y. U. Saito (2022): "Robots and Employment: Evidence from Japan, 1978-2017," *Journal of Labor Economics*, 0, null.

Argente, D., S. Baslandze, D. Hanley, and S. Moreira (2020): "Patents to Products: Product Innovation and Firm Dynamics," FRB Atlanta Working Paper 2020-4, Federal Reserve Bank of Atlanta.

Artuc, E., P. Bastos, and B. Rijkers (2023): "Robots, tasks, and trade," *Journal of International Economics*, 145, 103828.

Artuç, E., S. Chaudhuri, and J. McLaren (2010): "Trade shocks and labor adjustment: A structural empirical approach," *American economic review*, 100, 1008–1045.

Autor, D. H. and D. Dorn (2013): "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, 103, 1553–97.

Autor, D. H., F. Levy, and R. J. Murnane (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration*," *The Quarterly Journal of Economics*, 118, 1279–1333.

Beraja, M. and N. Zorzi (2022): "Inefficient Automation," NBER Working Papers 30154, National Bureau of Economic Research, Inc.

Bessen, J. E., M. Goos, A. Salomons, and W. Van den Berge (2019): "Automatic Reaction - What Happens to Workers at Firms that Automate?" *Boston Univ. School of Law, Law and Economics Research Paper*.

Bonfiglioli, A., R. Crinò, H. Fadinger, and G. Gancia (2020): "Robot Imports and Firm-Level Outcomes," Crc tr 224 discussion paper series, University of Bonn and University of Mannheim, Germany.

Bonfiglioli, A., R. Crinò, G. Gancia, and I. Papadakis (2021): "Robots, Offshoring and Welfare," CEPR Discussion Papers 16363, C.E.P.R. Discussion Papers.

Boustan, L. P., J. Choi, and D. Clingingsmith (2022): "Automation After the Assembly Line: Computerized Machine Tools, Employment and Productivity in the United States," Working Paper 30400, National Bureau of Economic Research.

Calel, R. (2020): "Adopt or Innovate: Understanding Technological Responses to Cap-and-Trade," *American Economic Journal: Economic Policy*, 12, 170–201.

Caliendo, L., M. Dvorkin, and F. Parro (2019): "Trade and labor market dynamics: General equilibrium analysis of the china trade shock," *Econometrica*, 87, 741–835.

Caunedo, J., D. Jaume, and E. Keller (2023): "Occupational Exposure to Capital-Embodied Technical Change," *American Economic Review*, 113, 1642–85.

Cette, G., A. Devillard, and V. Spiezia (2021): "The contribution of robots to productivity growth in 30 OECD countries over 1975–2019," *Economics Letters*, 200, 109762.

Cheng, H., L. A. Drozd, R. Giri, M. Taschereau-Dumouchel, and J. Xia (2021): "The Future of Labor: Automation and the Labor Share in the Second Machine Age," Working paper.

Ciccone, A. and G. Peri (2005): "Long-Run Substitutability Between More and Less Educated Workers: Evidence from U.S. States, 1950–1990," *The Review of Economics and Statistics*, 87, 652–663.

Colonnelli, E. and M. Prem (2019): "Corruption and firms," Documentos de Trabajo 017430, Universidad del Rosario.

Colonnelli, E., M. Prem, and E. Teso (2020): "Patronage and Selection in Public Sector Organizations," *American Economic Review*, 110, 3071–99.

Cooper, R. W. and J. C. Haltiwanger (2006): "On the nature of capital adjustment costs," *The Review of Economic Studies*, 73, 611–633.

Dauth, W., S. Findeisen, J. Suedekum, and N. Woessner (2021): "The Adjustment of Labor Markets to Robots," *Journal of the European Economic Association*, 19, 3104–3153.

de Souza, G. (2020): "The Labor Market Consequences of Appropriate Technology," Working paper.

De Souza, G. and H. Li (2022): "The employment consequences of anti-dumping tariffs: Lessons from Brazil," .

Dechezleprêtre, A., D. Hémous, M. Olsen, and C. Zanella (2021): "Induced automation: evidence from firm-level patent data," ECON - Working Papers 384, Department of Economics - University of Zurich.

Dix-Carneiro, R. (2014): "Trade liberalization and labor market dynamics," *Econometrica*, 82, 825–885.

Dix-Carneiro, R. and B. K. Kovak (2017): "Trade Liberalization and Regional Dynamics," *American Economic Review*, 107, 2908–46.

——— (2019): "Margins of labor market adjustment to trade," *Journal of International Economics*, 117, 125 – 142.

Furman, J. L., M. Nagler, and M. Watzinger (2021): "Disclosure and Subsequent Innovation: Evidence from the Patent Depository Library Program," *American Economic Journal: Economic Policy*, 13, 239–270.

Goldin, C. and L. F. Katz (1998): "The Origins of Technology-Skill Complementarity," *The Quarterly Journal of Economics*, 113, 693–732.

Graetz, G. and G. Michaels (2018): "Robots at Work," *The Review of Economics and Statistics*, 100, 753–768.

Hornstein, A., P. Krusell, and G. L. Violante (2005): "Chapter 20 - The Effects of Technical Change on Labor Market Inequalities," Elsevier, vol. 1 of *Handbook of Economic Growth*, 1275–1370.

Hubmer, J. and P. Restrepo (2021): "Not a Typical Firm: The Joint Dynamics of Firms, Labor Shares, and Capital–Labor Substitution," Working Paper 28579, National Bureau of Economic Research.

Humlum, A. (2021): "Robot Adoption and Labor Market Dynamics," Working paper.

Iacus, S. M., G. King, and G. Porro (2012): "Causal Inference without Balance Checking: Coarsened Exact Matching," *Political Analysis*, 20, 1–24.

Karabarbounis, L. and B. Neiman (2013): "The Global Decline of the Labor Share*," *The Quarterly Journal of Economics*, 129, 61–103.

Katz, L. F. and K. M. Murphy (1992): "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," *Quarterly Journal of Economics*, 107(1), 35–78.

Kleinman, B., E. Liu, and S. J. Redding (2023): "Dynamic spatial general equilibrium," *Econometrica*, 91, 385–424.

Koch, M., I. Manuylov, and M. Smolka (2021): "Robots and Firms," *The Economic Journal*, 131, 2553–2584.

Kogan, L., D. Papanikolaou, L. D. Schmidt, and B. Seegmiller (2023): "Technology and Labor Displacement: Evidence from Linking Patents with Worker-Level Data," Working Paper 31846, National Bureau of Economic Research.

Krusell, P., L. E. Ohanian, J.-V. Ríos-Rull, and G. L. Violante (2000): "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis," *Econometrica*, 68, 1029–1053.

Kugler, A. D., M. Kugler, L. Ripani, and R. Rodrigo (2020): "U.S. Robots and their Impacts in the Tropics: Evidence from Colombian Labor Markets," NBER Working Papers 28034, National Bureau of Economic Research, Inc.

Mann, K. and L. Püttmann (2023): "Benign Effects of Automation: New Evidence from Patent Texts," *The Review of Economics and Statistics*, 105, 562–579.

Parro, F. (2013): "Capital-skill complementarity and the skill premium in a quantitative model of trade," *American Economic Journal: Macroeconomics*, 5, 72–117.

Rodrigo, R. (2022): "Robot Adoption, Organizational Capital and the Productivity Paradox," Working Papers gueconwpa 22-22-03, Georgetown University, Department of Economics.

Su, C.-L. and K. L. Judd (2012): "Constrained optimization approaches to estimation of structural models," *Econometrica*, 80, 2213–2230.

Webb, M. (2019): "The Impact of Artificial Intelligence on the Labor Market," *Working Paper*, 3.

A Appendix for Simple Model

In this section, we derive the proofs for Section 2.

A.1 Equilibrium of Simple Model

The market-clearing condition for high-skilled workers is the following:

$$l_H = \frac{1}{w_H}\frac{(w_H)^{1-\sigma}}{(\Theta_T)^{1-\sigma}}\frac{(\Theta_T)^{-\theta}}{(P_R)^{-\theta}+(\Theta_T)^{-\theta}}\frac{p_A^{1-\psi}}{p_A^{1-\psi}+p_N^{1-\psi}}PY = A_H(w_H)^{\xi}. \tag{A.1}$$

The market-clearing condition for low-skilled workers implies that:

$$l_L = \frac{1}{w_L}\delta\frac{\left(\left([w_L]^{\delta}\left[P_T\right]^{1-\delta}\right)\right)^{1-\sigma}}{(\Theta_T)^{1-\sigma}}\frac{(\Theta_T)^{-\theta}}{(P_R)^{-\theta}+(\Theta_T)^{-\theta}}\frac{p_A^{1-\psi}}{p_A^{1-\psi}+p_N^{1-\psi}}PY = A_L(w_L)^{\xi}. \tag{A.2}$$

Without loss of generality, we normalize the economy's total output, PY, to 1. Therefore, the equilibrium is defined with wages $\{w_H, w_L\}$, such that Equations (A.1) and (A.2) hold.

A.2 Proofs of Simple Model

To derive proofs for the propositions in Section 2.2, we begin with the following two lemmas:

Lemma 1. The impact of tool and robot price shocks on the employment of high-skilled and low-skilled workers can be summarized as follows:

$$\begin{aligned}\operatorname{dlog}\ell_H =& -\frac{\Delta(1-s_{T,H})(1+\xi)(1-\delta)\xi}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta)+(1-s_{T,H})\delta(\xi+\sigma)\right]+(\xi+\sigma)(1+\xi+(\sigma-1)\delta)}\operatorname{dlog}P_T \\ &+\frac{(\Delta+\sigma-1+(1-s_A)(1-\psi))(1+\xi+(\sigma-1)\delta)\xi}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta)+(1-s_{T,H})\delta(\xi+\sigma)\right]+(\xi+\sigma)(1+\xi+(\sigma-1)\delta)}\operatorname{dlog}P_R,\end{aligned} \tag{A.3}$$

and

$$\mathrm{dlog}\,\ell_L = -\frac{(\Delta\left[(1-s_{T,H})(\xi+\sigma)+s_{T,H}(\sigma-1)\right]+(\sigma-1)(\xi+\sigma))\,(1-\delta)\xi}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta)+(1-s_{T,H})\delta(\xi+\sigma)\right]+(\xi+\sigma)(1+\xi+(\sigma-1)\delta)}\,\mathrm{dlog}\,P_T$$
$$+\frac{(\Delta+\sigma-1+(1-s_A)(1-\psi))(\xi+\sigma)\xi}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta)+(1-s_{T,H})\delta(\xi+\sigma)\right]+(\xi+\sigma)(1+\xi+(\sigma-1)\delta)}\,\mathrm{dlog}\,P_R, \tag{A.4}$$

in which $\Delta = 1-\sigma-(1-s_A)(1-\psi)+\left[(1-s_A)(1-\psi)+\theta\right]s_R$ summarizes the impact of tool price shocks on high-skilled workers. $s_{T,H}$ represents the share of tool technology expenditures devoted to high-skilled workers. s_A denotes the economy's expenditure share on automatable sectors. s_R denotes the expenditure share on robots for automatable tasks.

Proof of Lemma 1 Based on the definition of the input cost of the tools bundle, Θ_T, its log linearization is equal to the following:

$$\mathrm{dlog}(\Theta_T) = s_{T,H}\,\mathrm{dlog}(w_H)+(1-s_{T,H})\delta\,\mathrm{dlog}(w_L)+(1-s_{T,H})(1-\delta)\,\mathrm{dlog}(P_T).$$

Log linearize Equation (A.1):[53]

$$\begin{aligned}(1+\xi)\,\mathrm{dlog}(w_H) = {} & (1-\sigma)\,\mathrm{dlog}(w_H)-(1-\sigma)\,\mathrm{dlog}(\Theta_T)-\theta\,\mathrm{dlog}(\Theta_T)\\ & +\theta s_R\,\mathrm{dlog}(P_R)+\theta(1-s_R)\,\mathrm{dlog}(\Theta_T)\\ & +(1-\psi)s_R\,\mathrm{dlog}(P_R)+(1-\psi)(1-s_R)\,\mathrm{dlog}(\Theta_T)\\ & -s_A\left((1-\psi)s_R\,\mathrm{dlog}(P_R)+(1-\psi)(1-s_R)\,\mathrm{dlog}(\Theta_T)\right).\end{aligned} \tag{A.5}$$

Plug in $\mathrm{dlog}(\Theta_T)$ and collect terms:

$$\begin{aligned}&(\xi+\sigma+\Delta s_{T,H})\,\mathrm{dlog}\,w_H+(\Delta(1-s_{T,H})\delta)\,\mathrm{dlog}\,w_L\\ &= -\Delta(1-s_{T,H})(1-\delta)\,\mathrm{dlog}\,P_T-(1-\sigma-(1-s_A)(1-\psi)-\Delta)\,\mathrm{dlog}\,P_R,\end{aligned} \tag{A.6}$$

[53]In these derivations, we normalize GDP, PY, to 1.

where $\Delta = 1 - \sigma - (1-s_A)(1-\psi) + [(1-s_A)(1-\psi) + \theta]\, s_R$.

Log linearize Equation (A.2):

$$\begin{aligned}(1+\xi)\,\mathrm{dlog}(w_L) = {} & (1-\sigma)\delta\,\mathrm{dlog}(w_L) + (1-\sigma)(1-\delta)\,\mathrm{dlog}\,P_T - (1-\sigma)\,\mathrm{dlog}\,\Theta_T - \theta\,\mathrm{dlog}(\Theta_T) \\ & + \theta s_R\,\mathrm{dlog}(P_R) + \theta(1-s_R)\,\mathrm{dlog}(\Theta_T) \\ & + (1-\psi)s_R\,\mathrm{dlog}(P_R) + (1-\psi)(1-s_R)\,\mathrm{dlog}(\Theta_T) \\ & - s_A\left((1-\psi)s_R\,\mathrm{dlog}(P_R) + (1-\psi)(1-s_R)\,\mathrm{dlog}(\Theta_T)\right). \qquad \text{(A.7)}\end{aligned}$$

Plug in $\mathrm{dlog}(\Theta_T)$ and collect terms:

$$\begin{aligned}&(\Delta s_{T,H})\,\mathrm{dlog}\,w_H + (1+\xi+[\Delta(1-s_{T,H}) - 1 + \sigma]\,\delta)\,\mathrm{dlog}\,w_L \\ &= -(\Delta(1-s_{T,H}) - 1 + \sigma)(1-\delta)\,\mathrm{dlog}\,P_T - (1-\sigma-(1-s_A)(1-\psi)-\Delta)\,\mathrm{dlog}\,P_R. \quad \text{(A.8)}\end{aligned}$$

Combine Equations (A.6) and (A.8), eliminate $\mathrm{dlog}\,w_L$, and solve for $\mathrm{dlog}\,w_H$:

$$\begin{aligned}\mathrm{dlog}\,w_H = {} & -\frac{\Delta(1-s_{T,H})(1+\xi)(1-\delta)}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta) + (1-s_{T,H})\delta(\xi+\sigma)\right] + (\xi+\sigma)(1+\xi+(\sigma-1)\delta)}\,\mathrm{dlog}\,P_T \\ & + \frac{(\Delta+\sigma-1+(1-s_A)(1-\psi))(1+\xi+(\sigma-1)\delta)}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta) + (1-s_{T,H})\delta(\xi+\sigma)\right] + (\xi+\sigma)(1+\xi+(\sigma-1)\delta)}\,\mathrm{dlog}\,P_R. \qquad \text{(A.9)}\end{aligned}$$

Eliminate $\mathrm{dlog}\,w_H$, and solve for $\mathrm{dlog}\,w_L$:

$$\begin{aligned}\mathrm{dlog}\,w_L = {} & -\frac{\Delta\left[(1-s_{T,H})(\xi+\sigma) + s_{T,H}(\sigma-1)\right] + (\sigma-1)(\xi+\sigma)}{\Delta\left[(1-s_{T,H})\delta(\xi+\sigma) + s_{T,H}(1+\xi+(\sigma-1)\delta)\right] + (1+\xi+(\sigma-1)\delta)(\xi+\sigma)}(1-\delta)\,\mathrm{dlog}\,P_T \\ & + \frac{(\Delta+\sigma-1+(1-s_A)(1-\psi))(\xi+\sigma)}{\Delta\left[(1-s_{T,H})\delta(\xi+\sigma) + s_{T,H}(1+\xi+(\sigma-1)\delta)\right] + (1+\xi+(\sigma-1)\delta)(\xi+\sigma)}\,\mathrm{dlog}\,P_R. \qquad \text{(A.10)}\end{aligned}$$

These elasticities lead to the price shocks on the employment of high- and low-skilled workers presented in the text.

Lemma 2. In the denominators, $\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta) + (1-s_{T,H})\delta(\xi+\sigma)\right] + (\xi+\sigma)(1+\xi+(\sigma-1)\delta) > 0$.

Based on Lemma 2, we can determine whether robot and tool price shocks increase the employment of high-skilled and low-skilled workers by looking at the signs of the numerators in Lemma 1.

Proof of Lemma 2 Plug in $\Delta = 1 - \sigma - (1 - s_A)(1 - \psi) + [(1 - s_A)(1 - \psi) + \theta]\, s_R$ and collect terms:

$$
\begin{aligned}
&\Delta\left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right] + (\xi + \sigma)(1 + \xi + (\sigma - 1)\delta)\\
&= (1 - s_A)(\psi - 1)(1 - s_R)\left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right]\\
&+ \theta s_R\left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right]\\
&- (\sigma - 1)\left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right]\\
&+ (\xi + \sigma)(1 + \xi + (\sigma - 1)\delta)\\
&= (1 - s_A)(\psi - 1)(1 - s_R)\left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right]\\
&+ \theta s_R\left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right]\\
&- (\sigma - 1)\left[s_{T,H}(1 + \xi + (\sigma - 1)\delta)\right]\\
&+ (\xi + \sigma)(1 + \xi + s_{T,H}(\sigma - 1)\delta)\\
&= (1 - s_A)(\psi - 1)(1 - s_R)\left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right]\\
&+ \theta s_R\left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right]\\
&+ (\xi + 1)s_{T,H}(1 + \xi + s_{T,H}(\sigma - 1)\delta) + (\xi + \sigma)(1 - s_{T,H})(1 + \xi) > 0.
\end{aligned}
\tag{A.11}
$$

Equation (A.11) is positive because all terms in the equation are positive.

Proof of Proposition 1 Based on Lemma 2, in Equations (A.3) and (A.4), the sign of the impact of robot price changes on employment of both types depends on the sign of $(\Delta + \sigma - 1 + (1 - s_A)(1 - \psi))$. Plugging in $\Delta = 1 - \sigma - (1 - s_A)(1 - \psi) + [(1 - s_A)(1 - \psi) + \theta]\, s_R$, we show that $\Delta + (1 - s_A)(1 - \psi) + \sigma - 1 = \Bigg[\underbrace{(1 - s_A)(1 - \psi)}_{\text{Productivity Effect,}<0} + \underbrace{\theta}_{\text{Substitution Effect,}>0}\Bigg] s_R$.

Proof of Proposition 2 The sign of $\frac{\mathrm{dlog}\, l_L}{\mathrm{dlog}\, P_T}$ is determined by the sign of $-\left(\Delta\left[(1 - s_{T,H})(\xi + \sigma) + s_{T,H}(\sigma - 1)\right] + (\sigma - 1)(\xi + \sigma)\right)$. Plug in $\Delta = 1 - \sigma - (1 - s_A)(1 -$

$\psi) + [(1-s_A)(1-\psi)+\theta]\, s_R$ and collect terms:

$$
\begin{aligned}
&-\left(\Delta\left[(1-s_{T,H})(\xi+\sigma)+s_{T,H}(\sigma-1)\right]+(\sigma-1)(\xi+\sigma)\right)\\
&=\left((1-s_{T,H})(\xi+\sigma)+s_{T,H}(\sigma-1)\right)\left((1-\psi)(1-s_A)(1-s_R)-\theta s_R+\frac{(1-\sigma)s_{T,H}(\xi+1)}{(1-s_{T,H})(\xi+\sigma)+s_{T,H}(\sigma-1)}\right).
\end{aligned} \tag{A.12}
$$

Equation (A.12) is negative because all terms in the equation are negative.

Proof of Proposition 3 The sign of $\frac{\mathrm{dlog}\, l_H}{\mathrm{dlog}\, P_T}$ is determined by the sign of $-\Delta$, which can be further decomposed into the productivity effect, the reinstatement effect, and the substitution effect:

$$-\Delta = \underbrace{(1-s_A)(1-\psi)(1-s_R)}_{\text{Productivity Effect,}<0} + \underbrace{-\theta s_R}_{\text{Reinstatement Effect,}<0} + \underbrace{\sigma-1}_{\text{Substitution Effect,}>0}.$$

Proof of Proposition 4 Equivalently, we demonstrate that

$$\frac{\mathrm{dlog}\, w_H}{\mathrm{dlog}\, P_R} < \frac{\mathrm{dlog}\, w_L}{\mathrm{dlog}\, P_R}, \frac{\mathrm{dlog}\, \ell_H}{\mathrm{dlog}\, P_R} < \frac{\mathrm{dlog}\, \ell_L}{\mathrm{dlog}\, P_R}.$$

Assume that robots are substitutes for both low-skilled and high-skilled workers: $\Delta+\sigma-1+(1-s_A)(1-\psi)>0$. Plugging in Equations (A.9) and (A.10), low-skilled wages respond more to robot price shocks if and only if $0=\xi-\xi<(\sigma-1)(1-\delta)$, which is always true.

Furthermore, low-skilled employment responds more to robot price shocks if and only if $1=\frac{\xi}{\xi}<\frac{\sigma}{1-\delta+\sigma\delta}$, which is always true.

Proof of Proposition 5 Equivalently, we demonstrate that

$$\frac{\mathrm{dlog}\, w_H}{\mathrm{dlog}\, P_T} > \frac{\mathrm{dlog}\, w_L}{\mathrm{dlog}\, P_T}, \frac{\mathrm{dlog}\, \ell_H}{\mathrm{dlog}\, P_T} > \frac{\mathrm{dlog}\, \ell_L}{\mathrm{dlog}\, P_T}.$$

$\frac{\mathrm{dlog}\, w_H}{\mathrm{dlog}\, P_T} > \frac{\mathrm{dlog}\, w_L}{\mathrm{dlog}\, P_T}$ holds true if and only if $0=\xi-\xi<\frac{1}{1-s_{T,H}}\left[\frac{(\sigma-1)(\xi_1+\sigma)}{\Delta}+\sigma-1\right]$, which is always true. Additionally, $\frac{\mathrm{dlog}\, \ell_H}{\mathrm{dlog}\, P_T} > \frac{\mathrm{dlog}\, l_H}{\mathrm{dlog}\, P_T}$ holds true if and only if $1=\frac{\xi}{\xi}<\frac{1}{1-s_{T,H}}\left[\frac{(\sigma-1)(\xi+\sigma)}{\Delta}+\sigma-s_{T,H}\right]$, which is always true.

Corollary 1. The impact of tool and robot price shocks on (real) GDP can be summarized as follows:

$$\begin{aligned}\text{dlog}(Y) = &- \frac{s_A(1-s_R)(1-s_{T,H})(1-\delta)(\xi+\sigma)(\xi_2+1)}{\Delta\left[(1-s_{T,H})\delta(\xi+\sigma)+s_{T,H}(1+\xi+(\sigma-1)\delta)\right]+(1+\xi+(\sigma-1)\delta)(\xi+\sigma)}\,\text{dlog}\,P_T \\ &- \frac{s_As_R\left[(\xi+1)(\xi+1)+(\xi+1)(\sigma-1)s_{T,H}\delta+(\xi+1)(\sigma-1)(1-s_{T,H})\right]}{\Delta\left[(1-s_{T,H})\delta(\xi+\sigma)+s_{T,H}(1+\xi+(\sigma-1)\delta)\right]+(1+\xi+(\sigma-1)\delta)(\xi+\sigma)}\,\text{dlog}\,P_R.\end{aligned} \tag{A.13}$$

Equation (A.13) shows that a country's GDP can be increased by lowering the cost of either tools or robots.

Proof of Corollary 1 Since we normalize nominal GDP, $PY = 1$, the change in real GDP $\text{dlog}\,Y = -\,\text{dlog}\,P$. Note that:

$$\begin{aligned}\text{dlog}\,P = &\, s_As_R\,\text{dlog}\,P_R + s_A(1-s_R)s_{T,H}\,\text{dlog}\,w_H + s_A(1-s_R)(1-s_{T,H})\delta\,\text{dlog}\,w_L \\ &+ s_A(1-s_R)(1-s_{T,H})(1-\delta)\,\text{dlog}\,P_T.\end{aligned}$$

Plugging in $\text{dlog}\,w_H$ and $\text{dlog}\,w_L$ according to Equations (A.9) and (A.10) and collecting terms, we get Equation (A.13).

B Appendix for Empirical Analysis

B.1 Data

B.1.1 List of Wikipedia Articles

Robots. numerical control, industrial robot, cartesian coordinate robot, robotic arm, SCARA, articulated robot, parallel manipulator.

Tools. air hammer, angle grinder, metalworking hand tool, axe, mortiser, ball peen hammer, multiple lining tool, multi tool, beam compass, nail gun, belt sander, biscuit joiner, paniki, block plane, pickaxe, candle snuffer, piercing saw, card scraper, pliers, C-clamp, pneumatic torque wrench, ceramic tile cutter, podger spanner, porter cable, circular saw, pritchel, clamp, profile gauge, claw tool, corner chisel, random orbital sander, crowbar, reciprocating saw, die grinder, rivet gun, disc cutter, rotary hammer, domino joiner, drift pin, sabre saw, electric torque wrench, sally saw, F-clamp, sander, Fein multimaster RS, fuller, scissors, hacking knife, screw extractor, hackle, hacksaw, scriber, halligan bar, set square, hammer drill, set tool, hammer, shear, hand saw, shove knife, hand scraper, shovel, handspike, slide hammer, hand steel, snips, hand truck, spike maul, hardy tool, spline roller, hawk, stanley odd jobs, heat gun, stone and muller, honing steel, hook, tap wrench, hydraulic torque wrench, ice scraper, thread restorer, impact wrench, tongs, jackhammer, track saw, jigsaw, trash hook, knockout punch, upholstery hammer, laminate trimmer, vise, machete, wall chaser, machinist square, wire brush, magnetic switchable device, workbench, measuring rod, wrench.

Table B.1: List of Machines Included on the Classification

HS Code	Machine Description
8201 - 8205	**Hand Tools and Cutting Instruments:** *820110, 820130, 820140, 820150, 820190, 820210, 820220, 820231, 820239, 820240, 820291, 820299, 820310, 820320, 820330, 820340, 820411, 820412, 820420, 820510, 820520, 820530, 820540, 820551, 820559, 820570, 820590, 820600*
8412 - 8414, 8417, 8419, 8420, 8421	**Hydraulic, Pneumatic, and Mechanical Equipment:** *841221, 841229, 841231, 841239, 841280, 841290, 841319, 841320, 841330, 841350, 841360, 841370, 841381, 841391, 841410, 841420, 841430, 841440, 841451, 841459, 841460, 841480, 841490, 841720, 841780, 841790, 841919, 841932, 841939, 841940, 841950, 841981, 841989, 841990, 842091, 842099, 842119, 842121, 842122, 842123, 842129, 842131, 842139, 842191, 842199*
8406 - 8408, 8410, 8501, 8502, 8504	**Heat and Power Generation Equipment:** *840690, 840810, 840820, 840890, 841090, 850110, 850120, 850131, 850132, 850140, 850151, 850152, 850153, 850161, 850164, 850212, 850213, 850231, 850240, 850410, 850421, 850431, 850432, 850433, 850434, 850440, 850450, 850490*
8425 - 8430, 8474	**Industrial Machinery for Material Handling and Processing:** *842511, 842519, 842531, 842539, 842542, 842549, 842611, 842630, 842699, 842710, 842720, 842810, 842820, 842832, 842833, 842839, 842840, 842890, 842911, 842920, 842940, 842951, 843041, 847410, 847420, 847431, 847439, 847480, 847490*
8439 - 8441, 8445 - 8449	**Textile and Paper Machinery:** *843991, 843999, 844010, 844090, 844110, 844130, 844140, 844180, 844190, 844520, 844530, 844540, 844590, 844610, 844621, 844630, 844711, 844712, 844720, 844790, 844900*
8455 - 8463	**Machinery for Metalworking:** *845521, 845530, 845590, 845610, 845611, 845620, 845710, 845811, 845969, 846021, 846031, 846039, 846090, 846210, 846221, 846229, 846239, 846241, 846249, 846291, 846299, 846320, 846330, 846390*
8477 - 8479, 8486	**Rubber, Plastic, and Glass Processing Equipment:** *847710, 847720, 847730, 847740, 847751, 847759, 847780, 847790, 847810, 847890, 847910, 847940, 847950, 847960, 847981, 847982, 847989, 847990, 848620, 848640, 848690*
8432 - 8438	**Agricultural and Food Processing Machinery:** *843229, 843240, 843280, 843290, 843311, 843320, 843340, 843359, 843390, 843420, 843490, 843510, 843590, 843610, 843629, 843680, 843691, 843699, 843710, 843780, 843790, 843810, 843820, 843840, 843850, 843860, 843880, 843890*
9011 - 9032	**Measuring and Testing Instruments:** *901110, 901180, 901190, 901210, 901320, 901380, 901390, 901410, 901420, 901480, 901490, 901530, 901580, 901590, 901720, 901730, 901780, 901790, 902410, 902480, 902490, 902511, 902519, 902580, 902590, 902610, 902620, 902680, 902690, 902710, 902720, 902730, 902750, 902780, 902790, 902910, 902920, 902990, 903010, 903020, 903031, 903032, 903033, 903039, 903040, 903082, 903084, 903089, 903090, 903110, 903120, 903141, 903149, 903180, 903190, 903210, 903220, 903281, 903289, 903290*
8479, 8543	**Specialized Industrial Robots and Automation Equipment:** *847950, 854320, 854370, 854390*

B.1.2 Text Similarity

In this section, we describe in detail how we calculate the text similarity between Wikipedia articles and machines. Most of the steps follow Argente et al. (2020).

Parsing. To transform documents in vectors, we first need to determine what corresponds to each element of the vector. In our baseline application, we use words as tokens, i.e., 1-gram.

Lemmatization. To avoid counting conjugations of the same word as different words, we use the WordNet lexical database (wordnet.princeton.edu) to reduce words to their root forms by removing conjugations such as plural suffixes.

Selection. To avoid counting frequent and uninformative words, such as "the" and "and", we drop terms that appear in more than 80% of documents.

Vectorization. Following the previous steps, we can characterize each document with a vector of dummies for words it contains. Let $m \in \{1, ..., M\} = \mathcal{M}$ be the set for words in the document. Let c_{km} be a dummy variable taking 1 if document k contains word m. Therefore, document k can be represented by vector c_m with entries c_{km}.

Normalization. Rare words are more important for characterizing differences across documents than common words. To take that into account, we weight each word using total-frequency-inverse-document-frequency (tf-idf). Each term m of the dataset is weighted by

$$\omega_m = \log\left(\frac{K+1}{d_m+1}\right) + 1 \text{ where } d_m = \sum_k \mathbb{I}\left\{c_{km} > 0\right\}.$$

After weighting, each document is weighted by word frequency vector f_k with entries

$$f_{km} = \frac{\omega_m c_{km}}{\sqrt{\sum_{m'} (\omega_m c_{km})^2}}.$$

Similarity Scores. Using the normalized word vector for each document, f_k, we can calculate the similarity scores. The similarity between machine j and Wikipedia article w is given by

$$s_{jw} = \sum_{m \in \mathbb{M}} f_{jm} \times f_{pm}. \tag{B.1}$$

Final Classification. For machine j, the closest Wikipedia article is $w*_j = \arg\max_w s_{jw}$. We call j a robot if $w*_j$ is a Wikipedia article associated with automation and a tool otherwise.

B.1.3 Identifying Firms Importing Machines

Importers List. Another dataset enables us to identify the importing firm: the registry of importing firms. Every year, the Secretary of International Trade provides a list of all establishments that have imported any product that year. The list contains the name of the firm and its tax identifier. It does not contain any information on the product imported or its value.

Using the four datasets presented, we can identify a set of firms importing capital goods. We can identify a firm that is importing a capital good if this firm is the only importing firm in its sector and city in the year that the capital good is purchased. There are four steps to construct this dataset: 1) identify capital goods, 2) classify the sector of each capital good, 3) identify the city and sector of importers, and 4) identify unique firms in each sector, city and year pair.[54]

First, we classify capital goods according to a classification provided by the Secretary of International Trade. This list classifies each HS4 product as capital, intermediate, or consumer goods.

Second, we assign a sector to each good based on the sectoral imports dataset. We say that capital good i can be used in sector j if that sector has ever imported capital good i. Therefore, this list links every product to a set of sectors that accept that product in their production process.

In the third step, we link each importing establishment from the importers list database to a sector and city using RAIS. Because both datasets are at the establishment level, we

[54]This procedure was first used by de Souza (2020).

can link each importing establishment to a sector and city.

In the fourth and final step, we identify a set of firms importing capital goods. With importing data, the sector–product list, and the information on importing firms, we can identify some of the firms importing machines. From the import dataset together with the sector–product list, we know the location and sector of the firm making the purchase. Using the data created in step 3, we can identify a set of possible importers. In about 0.3% of these transactions, the exact importer is identified, Which gives us a set of 9,939 establishments engaging in 57,447 machine transactions.

B.1.4 Event-Study

Empirical Specification and Identification. To identify the effect of robots and tools at the firm level, we use a matched difference-in-differences.[55] For each firm that imports a robot or a tool, we find a set of control firms that match in terms of employment, number of workers with less education than a high-school diploma, age, and sector in the three years before the adoption of the machine.[56] With the matched group of firms at hand, We implement the following specification for firms adopting tools:

$$y_{i,g(i),t} = \sum_{j=-5}^{5} \beta_j \times \log\left(\text{Tools Import}_{i,g(i)}\right) + \mu_{g(i),t} + \mu_i + \epsilon_{i,g(i),t}, \tag{B.2}$$

where $\log\left(\text{Tools Import}_{i,g(i)}\right)$ is the log of tool imports first made by firm i, j is the distance in years to the first tool purchase, β_j is the correlation of firm-level outcomes j years to the machine import, and $y_{i,g(i),t}$ is an outcome of firm i, matched to group $g(i)$, in year t. If the firm is in the control group, i.e., it has not imported a tool, β_j is always zero. $\mu_{g(i),t}$ is a year–group fixed effect that captures common shocks to firms in the same sector and with similar labor market outcomes. μ_i is a firm fixed effect. We can write the model for robots in an equivalent way. We limit the sample to the set of firms that we observe importing tools or robots with a probability of 1.

[55]To match firms, we follow Iacus et al. (2012). A similar strategy has been used by Bessen et al. (2019), Calel (2020), and Furman et al. (2021), among many others.

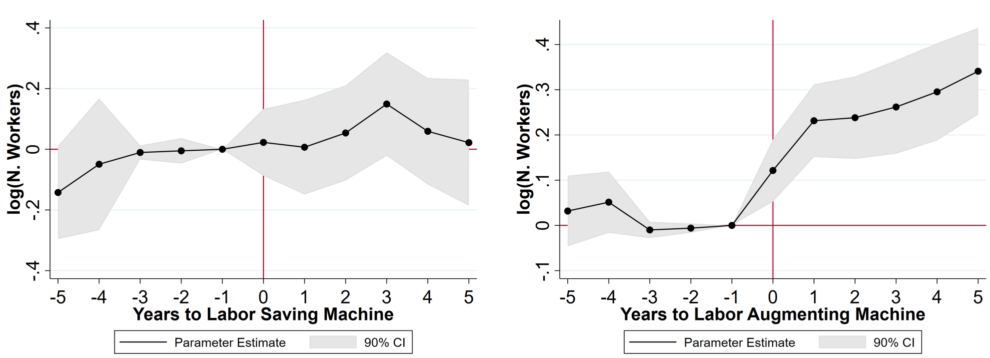
[56]Due to sample size limitations, we are unable to constrain the sample to machine importers only.

We interpret β_j as the correlation between tool adoption and labor outcome y. It is worth mentioning that the assumptions for a causal statement in this specification are very strong. The identifying assumption in difference-in-differences is of parallel trends. In other words, if it were not for the adoption of imported machines, the control and treatment groups would follow parallel paths. This assumption seems unreasonable in this scenario for two reasons: anticipation and shocks leading to the adoption of machines. First, the adoption of a new set of machines is not a surprise to the firm. Therefore, it is likely that firms adjust their size or employment composition before importing the machine. Second, the adoption of tools could itself be a response to labor market shocks affecting firms with particular characteristics. For instance, as shown by Bonfiglioli et al. (2020), demand shocks could induce firms to adopt robots. Therefore, we would not be able to separate the effect of a demand shock from the effect of the adoption of tools. Therefore, for these reasons, we do not expect the parallel trends assumption to hold in this case, despite parallel pre-period trends, and we interpret these results as correlations and not causal effects.

Results. Figure B.1 shows the correlation of robot and tool adoption with employment. Robot adoption is not significantly correlated with employment. At the same time, the import of tools is significantly correlated with increased employment at the firm level.

Figure B.1: Robots, Tools, and Employment

(a) Robots and Employment (b) Tools and Employment



Description: This figure shows the estimated coefficients of model B.2 on employment of firms adopting tools or robots. For each firm importing a tool or a robot, we create a control firm that matches it in terms of employment, share of high-school dropouts, age, and sector in the three years before the adoption of the machine. The sample is from 1997 to 2015. Standard errors are clustered at the firm level.

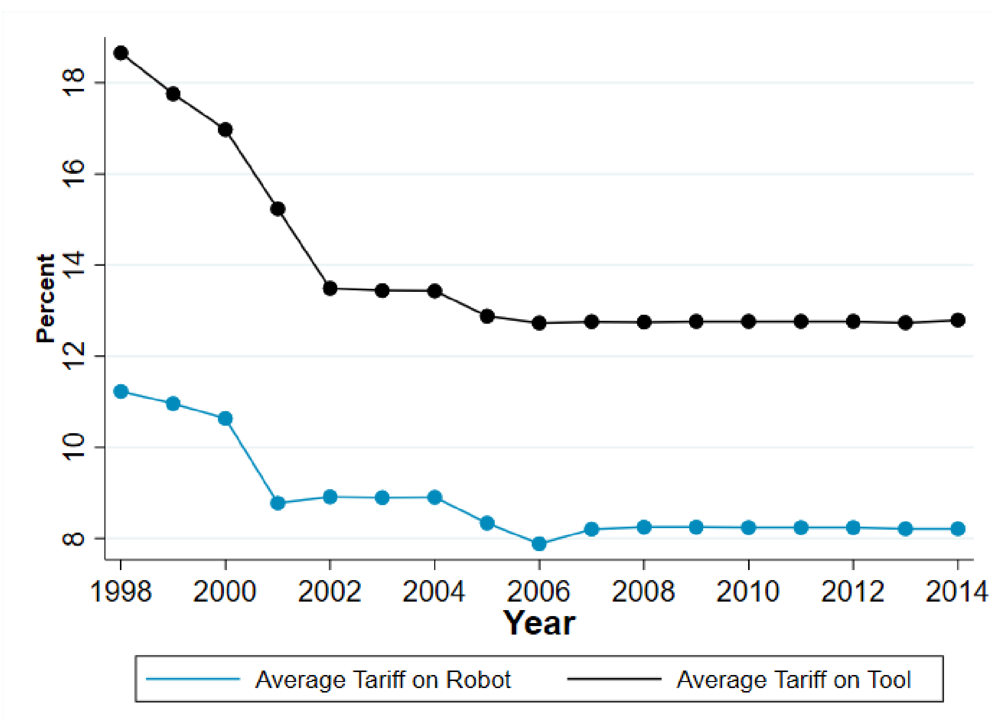
B.1.5 Other Tables and Figures

Table B.2: **Correlation between Words and Classification**

Dependent Variable: $\mathbb{I}(Robot)$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{I}$(*contain "automatic"*)	0.358***								
	(0.0724)								
$\mathbb{I}$(*contain "numeric"*)		0.537***							
		(0.111)							
$\mathbb{I}$(*contain "control"*)			0.209***						
			(0.0770)						
$\mathbb{I}$(*contain "robot"*)				0.933***					
				(0.250)					
$\mathbb{I}$(*contain "tool"*)					-0.0745				
					(0.0489)				
$\mathbb{I}$(*contain "hand"*)						-0.0498			
						(0.0418)			
$\mathbb{I}$(*contain "use"*)							-0.0411		
							(0.0468)		
$\mathbb{I}$(*contain "handle"*)								0.0224	
								(0.0777)	
$\mathbb{I}$(*contain "instrument"*)									0.0208
									(0.0456)
N	405	405	405	405	405	405	405	405	405
R^2	0.057	0.055	0.018	0.033	0.006	0.004	0.002	0.000	0.001

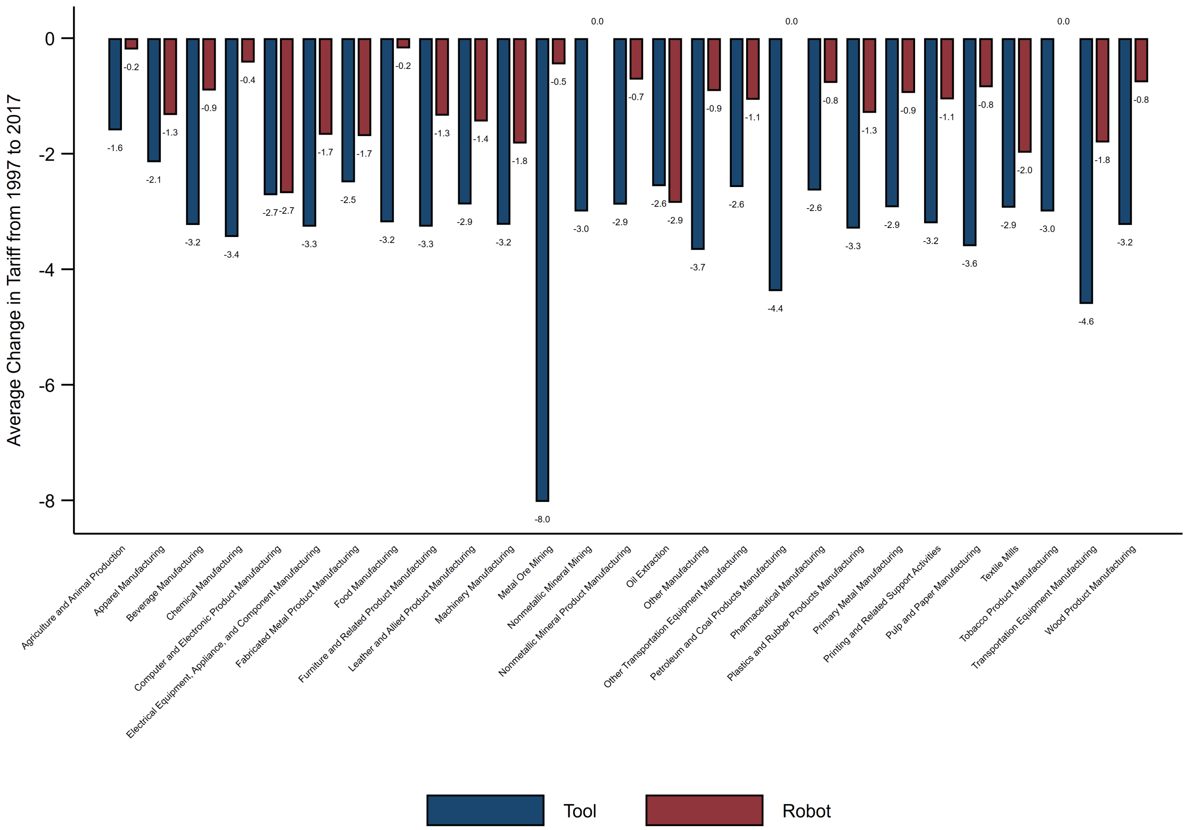
Description: This table shows the estimates of model: $\mathbb{I}_m\{Robot\} = \beta_x \mathbb{I}_m(contain\ "x") + \epsilon_m$, where $\mathbb{I}_m\{Robot\}$ is a dummy if machine m is a robot, $\mathbb{I}_m(contain\ "x")$ is a dummy if machine m has the word x, and β_x is the correlation between having a particular word and the probability of being classified as a robot.

Figure B.2: Tariff on Robots and Tools over Time



Description: This figure plots the average import tariff on robots and tools in Brazil overtime. Tariffs are weighted by the import share in 1997.

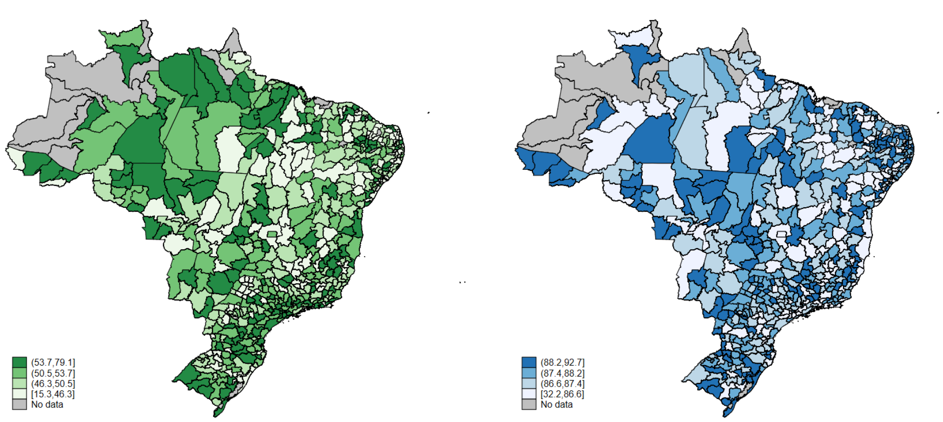
Figure B.3: Tariff Change in Robots and Tools Between 1997 and 2014



Description: This table shows the average tariff change in robots and tools on different 2-digit CNAE sectors.

Figure B.4: Manual and Routine Task Content Across Regions

(a) Routine Task Content (b) Manual Task Content



Description: This figure plots the average routine and manual task content in different microregions in Brazil in 1997. The routine task content for each occupation is constructed averaging the O*NET questions on the degree of automation and the importance of doing the same task. The manual task content for each occupation is constructed averaging all the O*NET questions related to the use of hand tools.

B.2 Empirics

Table B.3: Validation: Political Connections and Other Policies

	(1) $\Delta\log$ *Subsidized Loan*	(2) $\Delta\log$ *Vl. Federal Procurement*	(3) $\Delta\log$ *Campaign Contribution*	(4) $\Delta\log$ *International Import Price*	(5) $\Delta\log$ *International Export Price*
$IV_{r,s,t}^{tools}$	0.1411	-0.0556	-0.0767	-0.0019	0.0069*
	(0.1066)	(0.1227)	(0.0665)	(0.0035)	(0.0040)
$IV_{r,s,t}^{robots}$	-0.0063	0.1699	0.1239	0.0078	0.0067
	(0.1024)	(0.1248)	(0.0768)	(0.0074)	(0.0084)
N	56545	56545	56545	158944	70048
Controls	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (14) on outcomes related to prominent policies of the period. $IV_{r,s,t}^{tools}$ and $IV_{r,s,t}^{robots}$ are the instruments defined on 13 and 12, respectively. The difference is taken over the past 5 years. The controls are tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. In the first column, the left-hand side is the total loans made by the BNDES, in the second column the total federal procurement, in the third column it is the total campaign contributions made by firms, in the fourth column the price of imports, and in the last column the average price of exports. Standard errors are clustered at the region–sector level.

Table B.4: Validation: Pre-Period Labor Market Outcomes

	(1) $\Delta\log$ *Employment*	(2) $\Delta\log$ *Earnings*	(3) $\Delta\log$ *Wage Bill*	(4) $\Delta\log$ *Avg. Yrs. Edu.*	(5) $\Delta\log$ *H.S. Drop.*	(6) $\Delta\log$ *H.S. Complete*
$IV_{r,s,t}^{tools}$	0.0130	0.0407	-0.00783	0.0361	0.0783	0.00178
	(0.0144)	(0.0327)	(0.00720)	(0.0239)	(0.0590)	(0.0672)
$IV_{r,s,t}^{robots}$	-0.0182	-0.0279	-0.0146	0.0281	-0.0503	0.0170
	(0.0405)	(0.0734)	(0.0232)	(0.0697)	(0.0774)	(0.0777)
N	11692	11692	11582	11398	6758	4704
R^2	0.032	0.571	0.002	0.600	0.270	0.240
Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (14) on the growth rate of different labor market variables in the pre-period. $IV_{r,s,t}^{tools}$ and $IV_{r,s,t}^{robots}$ are the instruments defined on 13 and 12, respectively. The controls are tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. In the first column, the left-hand side is employment growth, in the second column it is average monthly wage, in the third column it is wage bill, in the fourth column it is average years of education, in the fifth column it is the number of workers with less education than a high-school diploma, and in the last column it is the number of workers with high-school. Standard errors are clustered at the region–sector level.

B.3 Empirical Results

Table B.5: First Stage with Inverse Hyperbolic Sine

	(1) ΔIHS robots	(2) ΔIHS robots	(3) ΔIHS robots	(4) ΔIHS tools	(5) ΔIHS tools	(6) ΔIHS tools
IV^{tools}	0.0426***	0.0367***	0.0392***	-0.0546***	-0.0676***	-0.0589***
	(0.0050)	(0.0050)	(0.0051)	(0.0081)	(0.0081)	(0.0082)
IV^{robots}	-0.2601***	-0.2622***	-0.2580***	-0.2879***	-0.2908***	-0.2808***
	(0.0132)	(0.0131)	(0.0132)	(0.0130)	(0.0128)	(0.0130)
N	204070	204069	204049	204070	204069	204049
R^2	0.318	0.339	0.388	0.505	0.529	0.555
F	124.564	124.001	209.476	139.537	144.064	221.878
Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Region FE	–	✓	–	–	✓	–
Sector FE	✓	✓	–	✓	✓	–
Reg-Sec FE	–	–	✓	–	–	✓

Description: This table shows the coefficients of the first stage, i.e., regressions (14) and (15) but instead of using the log of robots and tools plus one it uses the inverse hyperbolic sine. IV^{tools} is the interaction between the share of non-replaceable occupations and tariffs on tools in each sector. IV^{robots} is the interaction between the share of replaceable occupations and tariffs on robots in each sector. $Robots$ and $Tools$ denote the imports in dollars of robots and tools, respectively, in the past 5-years. The difference is taken over the past 5 years. All specifications have as controls the growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997 and year fixed effects. Columns 1 and 4 add a sector fixed effect, columns 2 and 5 have sector and region fixed effects, and columns 3 and 6 have sector–region fixed effects. Standard errors are clustered at the region–sector level.

Table B.6: First Stage with Dummy

	(1) $\Delta\mathbb{I}$ robots	(2) $\Delta\mathbb{I}$ robots	(3) $\Delta\mathbb{I}$ robots	(4) $\Delta\mathbb{I}$ tools	(5) $\Delta\mathbb{I}$ tools	(6) $\Delta\mathbb{I}$ tools
IV^{tools}	0.0005	0.0003	0.0009	-0.0065***	-0.0067***	-0.0055***
	(0.0006)	(0.0006)	(0.0007)	(0.0009)	(0.0009)	(0.0009)
IV^{robots}	-0.0264***	-0.0262***	-0.0245***	-0.0136***	-0.0133***	-0.0123***
	(0.0014)	(0.0014)	(0.0014)	(0.0009)	(0.0009)	(0.0010)
N	204070	204069	204049	204070	204069	204049
R^2	0.317	0.324	0.355	0.528	0.537	0.561
F	107.108	106.643	168.107	57.549	56.185	78.694
Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Region FE	–	✓	–	–	✓	–
Sector FE	✓	✓	–	✓	✓	–
Reg-Sec FE	–	–	✓	–	–	✓

Description: This table shows the coefficients of the first stage, i.e., regressions (14) and (15), in which the left-hand side is a dummy taking one if the market has imported at least one robot or tool in the past 5 years. IV^{tools} is the interaction between the share of non-replaceable occupations and tariffs on tools in each sector. IV^{robots} is the interaction between the share of replaceable occupations and tariffs on robots in each sector. $\mathbb{I}\{Robots\}$ and $\mathbb{I}\{Tools\}$ is a dummy taking one if there is at least one import of robot or tools, respectively, in the past 5-years. The difference is taken over the past 5 years. All specifications have as controls the growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997 and year fixed effects. Columns 1 and 4 add a sector fixed effect, columns 2 and 5 have sector and region fixed effects, and columns 3 and 6 have sector–region fixed effects. Standard errors are clustered at the region–sector level.

Table B.7: First Stage without Tools Instrument

	(1) Δlog robots	(2) Δlog robots	(3) Δlog robots	(4) Δlog tools	(5) Δlog tools	(6) Δlog tools
IV^{robots}	-0.2261***	-0.2301***	-0.2266***	-0.2948***	-0.3021***	-0.2892***
	(0.0122)	(0.0121)	(0.0122)	(0.0122)	(0.0121)	(0.0123)
N	204070	204069	204049	204070	204069	204049
R^2	0.315	0.337	0.388	0.497	0.523	0.549
F	164.133	165.679	267.169	175.127	177.888	264.715
Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Region FE	–	✓	–	–	✓	–
Sector FE	✓	✓	–	✓	✓	–
Reg-Sec FE	–	–	✓	–	–	✓

Description: This table shows the coefficients of the first stage, i.e., regressions (14), but without controlling for tools, IV^{tools}. IV^{robots} is the interaction between the share of replaceable occupations and tariffs on robots in each sector. *Robots* denote the imports in dollars of robots in the past 5-years. The difference is taken over the past 5 years. All specifications have as controls the growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997 and year fixed effects. Columns 1 and 4 add a sector fixed effect, columns 2 and 5 have sector and region fixed effects, and columns 3 and 6 have sector–region fixed effects. Standard errors are clustered at the region–sector level.

Table B.8: Employment and Robots without Controlling for Tools

	(1) Δlog *Employment*	(2) Δlog *Employment*	(3) Δlog *Employment*	(4) Δlog *Employment*	(5) Δlog *Employment*	(6) Δlog *Employment*
Δ log(Robots)	0.0003	0.0050	0.0046	0.0047	0.0037	0.0222
	(0.0059)	(0.0057)	(0.0061)	(0.0182)	(0.0179)	(0.0180)
N	239581	204070	204069	204070	204069	204049
Controls	–	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Region FE	–	–	✓	–	✓	–
Sector FE	–	–	–	✓	✓	–
Reg-Sec FE	–	–	–	–	–	✓

Description: This table shows the coefficients of regression (10) on employment but without controlling for tools. Δ log(Robots) is instrumented by IV^{tools}. *Robots* denote the imports in dollars of robots in the past 5 years. The difference is taken over the past 5 years. All specifications include as control year fixed effects. In column 1, there are no controls other than year fixed effects. Column 2 adds the baseline controls, i.e., the growth rate of employment between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, and the average manual task content in 1997. Column 3 adds region fixed effect to the controls. Column 4 adds sector fixed effect to the controls. Column 5 includes as controls the baseline controls, region FE, and sector FE. Column 6 includes sector–region FEs and the baseline controls. Standard errors are clustered at the region–sector level.

B.3.1 Robot and Tool Imports as Instrument and Comparison to the Literature

In this section, we follow the procedure adopted by Acemoglu and Restrepo (2020) and Dauth et al. (2021), among others, and instrument robot and tool adoption with their import by other countries. We find that the main results remain the same. Moreover, if tools are removed from the specification, the estimated effect of robots is upward-biased and closer to zero, which is similar to what has been found in the literature.

First Stage. The instrument is given by the imports of robots and tools by the US or Europe. The first stage is:

$$\Delta log(robots_{r,s,t}) = \pi^W_{1,1}\Delta IMP^{robots}_{s,t} + \pi^W_{1,2}\Delta IMP^{tools}_{s,t} + \epsilon_{r,s,t} \tag{B.3}$$

$$\Delta log(tools_{r,s,t}) = \pi^W_{2,1}\Delta IMP^{robots}_{s,t} + \pi^W_{2,2}\Delta IMP^{tools}_{s,t} + \epsilon_{r,s,t}, \tag{B.4}$$

where $IMP^{robots}_{s,t}$ are the imports of robots by the US and Europe assigned to sector s in the past 5 years. Similarly, $IMP^{tools}_{s,t}$ is the imports of tools by the US and Europe. The identifying assumption is that the increased adoption of machines by these countries is driven by supply side factors, such as a decrease in the machines' price or increase in their quality.

Results. Table B.9 shows that the imports of robots and tools in Brazil are associated with their imports in the US and Europe. In most specifications, the cross-elasticities are also large and significant, implying that increased imports of robots (tools) in developed countries leads to higher adoption of tools (robots) in Brazil. As before, this implies that removing tools from specification (10) will lead to a downward bias in the estimated effect of robots.

Table B.9: First Stage with Imports by Other Countries as Instrument

	(1) Δlog *Robots*	(2) Δlog *Robots*	(3) Δlog *Robots*	(4) Δlog *Tool*	(5) Δlog *Tool*	(6) Δlog *Tool*
IMP^{tools}	0.0979***	0.1210***	0.1260***	0.1453*	0.1729**	0.1502**
	(0.0304)	(0.0296)	(0.0276)	(0.0856)	(0.0702)	(0.0665)
IMP^{robots}	0.8662***	1.2012***	1.2046***	0.3118***	-0.0696	0.0301
	(0.0803)	(0.0375)	(0.0340)	(0.1115)	(0.0572)	(0.0509)
N	189456	132513	132512	189456	132513	132512
R^2	0.104	0.052	0.105	0.055	0.055	0.119
F	64.366	238.328	279.666	5.719	8.283	7.825
Controls	–	✓	✓	–	✓	✓
Year FE	–	✓	✓	–	✓	✓
Region FE	–	–	✓	–	–	✓

Description: This table shows the coefficients of the first stage, i.e., regressions (B.3) and (B.4). IMP^{tools} and $IMP^{robots}_{s,t}$ are the imports of tools and robots by the US and Europe assigned to each sector in the past 5 years. *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. Columns 1 and 4 do not have any controls. Columns 2 and 5 have as controls the growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Columns 3 and 6 add region fixed effects to the baseline controls. Standard errors are clustered at the region–sector level.

Table B.10 shows the effect of robots and tools on the labor market when using imports by other countries as instruments. It is still true that tools increase employment and earnings, whereas robots decrease them. Compared to the elasticities identified in Section 6, the effect of tools is larger and the effect of robots smaller. Moreover, tools also positively affect the employment of workers with college or more education. Still, the estimated effect of robots is larger than previously found on the literature.

Table B.10: Effect of Robots and Tools with Imports by Other Countries as Instrument

	(1) Δ*log* *Employment*	(2) Δ*log* *Earnings*	(3) Δ*log* *Wage Bill*	(4) Δ*log* *H.S. Drop.*	(5) Δ*log* *H.S. Complete*	(6) Δ*log* *College or More*
Δ log(Tools)	0.643***	0.188***	0.831***	0.600***	0.0325	0.383***
	(0.207)	(0.0611)	(0.258)	(0.220)	(0.111)	(0.137)
Δ log(Robots)	-0.119***	-0.0253**	-0.144***	-0.181***	-0.0431**	0.0502*
	(0.0427)	(0.0123)	(0.0530)	(0.0404)	(0.0201)	(0.0272)
N	189456	189456	189456	178163	161605	101569
R^2	-2.037	-2.118	-2.792	-1.868	-0.004	-0.689
Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on the labor market using as the instrument the imports of robots and tools by the US and Europe. Δ log(Tools) and Δ log(Robots) are instrumented by imports of robots and tools by other countries, as defined in (B.3) and (B.4). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.11 shows the bias arising from removing tools from the main empirical model. Instrumenting robots with their imports by other countries only identifies the net effect of robots. This happens because, according to the results in Table B.9, the adoption of robots by other countries also increases the adoption of tools in Brazil. When tools are removed from the main empirical model, only the net effect is identified. The estimates found are much smaller and closer in magnitude to what Acemoglu and Restrepo (2020) found.

Table B.11: Effect of Robots with Imports by Other Countries as Instrument and Without Controlling for Tools

	(1) Δlog *Employment*	(2) Δlog *Earnings*	(3) Δlog *Wage Bill*	(4) Δlog *H.S. Drop.*	(5) Δlog *H.S. Complete*	(6) Δlog *College or More*
Δ log(Robots)	-0.0483**	-0.00470	-0.0530**	-0.127***	-0.0421**	0.0166
	(0.0195)	(0.00500)	(0.0213)	(0.0195)	(0.0197)	(0.0200)
N	189456	189456	189456	178163	161605	101569
R^2	-0.006	-0.000	-0.005	-0.027	-0.003	0.000
Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) without controlling for the adoption of tools. $\Delta\log(tools)$ is instrumented by imports of robots by other countries. *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

B.3.2 Tariff Instrument

Table B.12: Tariff IV: Employment, Robots, and Tools

	(1) Δlog *Employment*	(2) Δlog *Employment*	(3) Δlog *Employment*	(4) Δlog *Employment*	(5) Δlog *Employment*	(6) Δlog *Employment*
Δ log(Tools)	0.1411***	0.1355***	0.1314***	0.1727***	0.1644***	0.1804***
	(0.0200)	(0.0211)	(0.0201)	(0.0259)	(0.0239)	(0.0250)
Δ log(Robots)	-0.0957***	-0.0878***	-0.0781***	-0.2355***	-0.2272***	-0.2264***
	(0.0146)	(0.0147)	(0.0133)	(0.0355)	(0.0343)	(0.0342)
N	266304	204812	204811	204812	204811	204791
Controls	–	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Region FE	–	–	✓	–	✓	–
Sector FE	–	–	–	✓	✓	–
Reg-Sec FE	–	–	–	–	–	✓

Description: This table shows the coefficients of regression (10) on employment. Δ log(Tools) and Δ log(Robots) are instrumented by the average tariffs on robots and tools, as described in 11. *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. All specifications have year fixed effects. In column 1, there are no controls other than year fixed effects. In column 1 there are no controls. Column 2 adds the baseline controls, i.e., growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Column 3 adds region FE to the baseline controls. Column 4 adds sector FE to the baseline controls. Column 5 includes as controls the baseline controls, region FE, and sector FE. Column 6 includes sector–region FEs and the baseline controls. Standard errors are clustered at the region–sector level.

Table B.13: Tariff IV: Labor Market, Robots, and Tools

	(1) Δlog *Employment*	(2) Δlog *Earnings*	(3) Δlog *Wage Bill*	(4) Δlog *H.S. Drop.*	(5) Δlog *H.S. Complete*	(6) Δlog *College or More*
Δ log(Tools)	0.164***	0.0391***	0.203***	0.0224***	0.159***	0.0782***
	(0.0239)	(0.00743)	(0.0273)	(0.00532)	(0.0242)	(0.0266)
Δ log(Robots)	-0.227***	-0.0322***	-0.260***	-0.0186**	-0.234***	-0.0252
	(0.0343)	(0.0108)	(0.0392)	(0.00754)	(0.0347)	(0.0283)
N	204811	204811	204811	202941	194872	116352
R^2	-0.282	-0.130	-0.326	-0.090	-0.291	-0.030
Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on labor market outcomes using tariffs as instrument. Δ log(Tools) and Δ log(Robots) are instrumented by the average tariffs on robots and tools. *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.14: Tariff IV: Occupations, Robots, and Tools

	(1) Δlog *Managers*	(2) Δlog *HS Professionals*	(3) Δlog *Technical Workers*	(4) Δlog *Adm Workers*	(5) Δlog *Operational Workers*
Δ log(Tools)	0.0037	-0.0003	0.0815***	0.0927***	0.2091***
	(0.0276)	(0.0393)	(0.0300)	(0.0243)	(0.0319)
Δ log(Robots)	0.0235	0.0229	-0.0265	-0.1234***	-0.2223***
	(0.0241)	(0.0329)	(0.0262)	(0.0277)	(0.0402)
N	46422	20288	72857	134159	149619
R^2	-0.002	-0.002	-0.033	-0.084	-0.380
Controls	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on the employment of different occupations using tariffs as instrument. Δ log(Tools) and Δ log(Robots) are instrumented by the average tariffs on robots and tools. *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

B.3.3 Outliers

Table B.15: Effect of Tools and Robots on Employment Dropping Top and Bottom 0.1% of Tariff Changes

	(1)	(2)	(3)	(4)	(5)	(6)
	Δlog *Employment*	Δlog *Employment*	Δlog *Employment*	Δlog *Employment*	Δlog *Employment*	Δlog *Employment*
Δ log(Tools)	0.1454***	0.1467***	0.1427***	0.1722***	0.1639***	0.1850***
	(0.0214)	(0.0217)	(0.0207)	(0.0257)	(0.0236)	(0.0249)
Δ log(Robots)	-0.1052***	-0.0987***	-0.0880***	-0.2181***	-0.2096***	-0.2127***
	(0.0158)	(0.0154)	(0.0139)	(0.0330)	(0.0318)	(0.0324)
N	239162	203745	203744	203745	203744	203724
R^2	-0.165	-0.171	-0.161	-0.292	-0.266	-0.365
Controls	–	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Region FE	–	–	✓	–	✓	–
Sector FE	–	–	–	✓	✓	–
Reg-Sec FE	–	–	–	–	–	✓

Description: This table shows the coefficients of regression (10) on employment. Sectors with tariff changes in the top and bottom 0.1% are dropped. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. All specifications have year fixed effects. In column 1, there are no controls other than year fixed effects. Column 2 adds the baseline controls, i.e., the growth rate of employment between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, and the average manual task content in 1997. Column 3 adds region fixed effect to the controls. Column 4 adds sector fixed effect to the controls. Column 5 includes as controls the baseline controls, region FE, and sector FE. Column 6 includes sector–region FEs and the baseline controls. Standard errors are clustered at the region–sector level.

Table B.16: Effect of Tools and Robots on Employment Dropping Top and Bottom 0.5% of Tariff Changes

	(1)	(2)	(3)	(4)	(5)	(6)
	Δlog *Employment*	Δlog *Employment*	Δlog *Employment*	Δlog *Employment*	Δlog *Employment*	Δlog *Employment*
Δ log(Tools)	0.1663***	0.1704***	0.1637***	0.1799***	0.1731***	0.1909***
	(0.0228)	(0.0232)	(0.0217)	(0.0264)	(0.0241)	(0.0255)
Δ log(Robots)	-0.1196***	-0.1146***	-0.1003***	-0.2643***	-0.2571***	-0.2556***
	(0.0166)	(0.0163)	(0.0144)	(0.0378)	(0.0369)	(0.0376)
N	236673	201597	201596	201597	201596	201575
R^2	-0.216	-0.243	-0.221	-0.405	-0.359	-0.450
Controls	–	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Region FE	–	–	✓	–	✓	–
Sector FE	–	–	–	✓	✓	–
Reg-Sec FE	–	–	–	–	–	✓

Description: This table shows the coefficients of regression (10) on employment. Sectors with tariff changes in the top and bottom 0.5% are dropped. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. All specifications have year fixed effects. In column 1, there are no controls other than year fixed effects. Column 2 adds the baseline controls, i.e., the growth rate of employment between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, and the average manual task content in 1997. Column 3 adds region fixed effect to the controls. Column 4 adds sector fixed effect to the controls. Column 5 includes as controls the baseline controls, region FE, and sector FE. Column 6 includes sector–region FEs and the baseline controls. Standard errors are clustered at the region–sector level.

Table B.17: Effect of Tools and Robots on Labor Market Dropping Top and Bottom 0.1% of Tariff Changes

	(1) Δlog *Employment*	(2) Δlog *Earnings*	(3) Δlog *Wage Bill*	(4) Δlog *H.S. Drop.*	(5) Δlog *H.S. Complete*	(6) Δlog *College or More*
Δ log(Tools)	0.164***	0.0402***	0.204***	0.157***	0.0874***	0.0386
	(0.0236)	(0.00739)	(0.0272)	(0.0238)	(0.0266)	(0.0251)
Δ log(Robots)	-0.210***	-0.0366***	-0.246***	-0.212***	-0.0282	-0.0146
	(0.0318)	(0.0100)	(0.0365)	(0.0318)	(0.0276)	(0.0232)
N	203744	203744	203744	193965	116166	75758
R^2	-0.266	-0.140	-0.318	-0.264	-0.039	-0.002
Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on labor market outcomes. Sectors with tariff changes in the top and bottom 0.1% are dropped. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.18: Effect of Tools and Robots on Labor Market Dropping Top and Bottom 0.5% of Tariff Changes

	(1) Δlog *Employment*	(2) Δlog *Earnings*	(3) Δlog *Wage Bill*	(4) Δlog *H.S. Drop.*	(5) Δlog *H.S. Complete*	(6) Δlog *College or More*
Δ log(Tools)	0.173***	0.0433***	0.216***	0.157***	0.0962***	0.0714***
	(0.0241)	(0.00749)	(0.0277)	(0.0242)	(0.0267)	(0.0255)
Δ log(Robots)	-0.257***	-0.0447***	-0.302***	-0.255***	-0.0380	-0.0337
	(0.0369)	(0.0116)	(0.0424)	(0.0370)	(0.0310)	(0.0272)
N	201596	201596	201596	191912	114991	74991
R^2	-0.329	-0.168	-0.391	-0.307	-0.049	-0.022
Year FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on labor market outcomes. Sectors with tariff changes in the top and bottom 0.5% are dropped. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.19: Effect of Tools and Robots on Different Occupations Dropping Top and Bottom 0.1% of Tariff Changes

	(1) Δlog *Managers*	(2) Δlog *HS Professionals*	(3) Δlog *Technical Workers*	(4) Δlog *Adm Workers*	(5) Δlog *Operational Workers*
Δ log(Tools)	0.0141	0.0129	0.0766***	0.1006***	0.2272***
	(0.0270)	(0.0377)	(0.0295)	(0.0241)	(0.0332)
Δ log(Robots)	0.0142	0.0198	-0.0102	-0.1187***	-0.1821***
	(0.0231)	(0.0306)	(0.0253)	(0.0267)	(0.0383)
N	46358	20250	72741	133922	149395
R^2	-0.001	-0.002	-0.034	-0.089	-0.413
Controls	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment of different occupational groups. Sectors with tariff changes in the top and bottom 0.1% are dropped. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.20: Effect of Tools and Robots on Different Occupations Dropping Top and Bottom 0.5% of Tariff Changes

	(1) Δlog *Managers*	(2) Δlog *HS Professionals*	(3) Δlog *Technical Workers*	(4) Δlog *Adm Workers*	(5) Δlog *Operational Workers*
Δ log(Tools)	0.0309	0.0479	0.1184***	0.1169***	0.2590***
	(0.0260)	(0.0463)	(0.0310)	(0.0245)	(0.0350)
Δ log(Robots)	0.0030	0.0328	-0.0035	-0.1516***	-0.2080***
	(0.0255)	(0.0403)	(0.0300)	(0.0309)	(0.0445)
N	45900	20042	71975	132519	147778
R^2	-0.005	-0.024	-0.090	-0.131	-0.535
Year FE	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment of different occupational groups. Sectors with tariff changes in the top and bottom 0.5% are dropped. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

B.3.4 Controls

Table B.21: Effect of Tools and Robots on Different Educational Groups - Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Δlog *H.S. Drop.*	Δlog *Wage H.S. Drop.*	Δlog *H.S. Complete*	Δlog *Wage H.S. Complete*	Δlog *College*	Δlog *Wage College*
Δ log(Tools)	0.1398***	0.0427***	0.0566**	0.0160	0.0213	0.0101
	(0.0222)	(0.0072)	(0.0242)	(0.0102)	(0.0212)	(0.0111)
Δ log(Robots)	-0.1204***	-0.0400***	-0.0143	-0.0254***	0.0065	-0.0087
	(0.0157)	(0.0052)	(0.0148)	(0.0063)	(0.0123)	(0.0063)
N	194272	194272	116352	116352	75879	75879
Year FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment and earnings of different educational groups. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Columns 1 and 2 show the effect of robots and tools on employment and earnings of workers that have less education than a high-school diploma. Columns 3 and 4 show the effect on workers with high-school diploma. Columns 5 and 6 show the effect on workers with at least some college education. Standard errors are clustered at the region–sector level.

Table B.22: Effect of Tools and Robots on Different Educational Groups - Year and Sector Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Δlog *H.S. Drop.*	Δlog *Wage H.S. Drop.*	Δlog *H.S. Complete*	Δlog *Wage H.S. Complete*	Δlog *College*	Δlog *Wage College*
Δ log(Tools)	0.1830***	0.0561***	0.0966***	0.0142	0.0539**	0.0211
	(0.0269)	(0.0085)	(0.0287)	(0.0115)	(0.0261)	(0.0133)
Δ log(Robots)	-0.2409***	-0.0587***	-0.0394	-0.0267**	-0.0248	-0.0108
	(0.0340)	(0.0107)	(0.0286)	(0.0115)	(0.0235)	(0.0121)
N	194272	194272	116352	116352	75879	75879
Year FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment and earnings of different educational groups. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, and region fixed effects. Columns 1 and 2 show the effect of robots and tools on employment and earnings of workers that have less education than a high-school diploma. Columns 3 and 4 show the effect on workers with a high-school diploma. Columns 5 and 6 show the effect on workers with at least some college education. Standard errors are clustered at the region–sector level.

Table B.23: Labor Market, Robots, and Tools – Market Fixed Effects

	(1) Δlog *H.S. Drop.*	(2) Δlog *Wage H.S. Drop.*	(3) Δlog *H.S. Complete*	(4) Δlog *Wage H.S. Complete*	(5) Δlog *College*	(6) Δlog *Wage College*
Δ log(Tools)	0.1923***	0.0297***	0.1003***	0.0074	0.0463*	0.0241*
	(0.0256)	(0.0071)	(0.0269)	(0.0105)	(0.0248)	(0.0130)
Δ log(Robots)	-0.2371***	-0.0320***	-0.0359	-0.0218**	-0.0199	-0.0127
	(0.0329)	(0.0092)	(0.0275)	(0.0108)	(0.0225)	(0.0119)
N	194240	194240	116335	116335	75849	75849
Year FE	✓	✓	✓	✓	✓	✓
Reg-Sec FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment and earnings of different educational groups. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, and region-sector fixed effects. Columns 1 and 2 show the effect of robots and tools on employment and earnings of workers that have less education than a high-school diploma. Columns 3 and 4 show the effect on workers with a high-school diploma. Columns 5 and 6 show the effect on workers with at least some college education. Standard errors are clustered at the region–sector level.

Table B.24: Labor Market, Robots, and Tools – Year × Initial Employment

	(1) Δlog *H.S. Drop.*	(2) Δlog *Wage H.S. Drop.*	(3) Δlog *H.S. Complete*	(4) Δlog *Wage H.S. Complete*	(5) Δlog *College*	(6) Δlog *Wage College*
Δ log(Tools)	0.1649***	0.0418***	0.0889***	0.0080	0.0456*	0.0198
	(0.0242)	(0.0073)	(0.0266)	(0.0105)	(0.0251)	(0.0127)
Δ log(Robots)	-0.2184***	-0.0448***	-0.0303	-0.0218**	-0.0203	-0.0092
	(0.0326)	(0.0098)	(0.0278)	(0.0110)	(0.0234)	(0.0121)
N	194269	194269	116352	116352	75878	75878
Year FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment and earnings of different educational groups. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the initial level of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, sector fixed effects, and initial employment interacted with year. Columns 1 and 2 show the effect of robots and tools on employment and earnings of workers that have less education than a high-school diploma. Columns 3 and 4 show the effect on workers with a high-school diploma. Columns 5 and 6 show the effect on workers with at least some college education. Standard errors are clustered at the region–sector level.

Table B.25: Labor Market, Robots, and Tools – Year × Pre-period Growth

	(1) Δlog *H.S. Drop.*	(2) Δlog *Wage H.S. Drop.*	(3) Δlog *H.S. Complete*	(4) Δlog *Wage H.S. Complete*	(5) Δlog *College*	(6) Δlog *Wage College*
Δ log(Tools)	0.1348***	0.0435***	0.0842***	0.0063	0.0485**	0.0235*
	(0.0227)	(0.0071)	(0.0262)	(0.0102)	(0.0244)	(0.0123)
Δ log(Robots)	-0.1878***	-0.0422***	-0.0357	-0.0171*	-0.0367*	-0.0145
	(0.0298)	(0.0093)	(0.0266)	(0.0102)	(0.0220)	(0.0112)
N	194269	194269	116352	116352	75878	75878
Year FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment and earnings of different educational groups. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997 interacted with year fixed effect, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. Columns 1 and 2 show the effect of robots and tools on employment and earnings of workers that have less education than a high-school diploma. Columns 3 and 4 show the effect on workers with a high-school diploma. Columns 5 and 6 show the effect on workers with at least some college education. Standard errors are clustered at the region–sector level.

Table B.26: Labor Market, Robots, and Tools – Other Inputs

	(1) Δlog *H.S. Drop.*	(2) Δlog *Wage H.S. Drop.*	(3) Δlog *H.S. Complete*	(4) Δlog *Wage H.S. Complete*	(5) Δlog *College*	(6) Δlog *Wage College*
Δ log(Tools)	0.1389***	0.0421***	0.0880***	0.0059	0.0407	0.0306*
	(0.0278)	(0.0087)	(0.0324)	(0.0124)	(0.0307)	(0.0156)
Δ log(Robots)	-0.1609***	-0.0362***	-0.0289	-0.0177*	-0.0163	-0.0154
	(0.0292)	(0.0092)	(0.0276)	(0.0106)	(0.0238)	(0.0122)
N	169565	169565	106189	106189	72376	72376
Year FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment and earnings of different educational groups. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, import of other inputs, year fixed effects, region fixed effects, and sector fixed effects. Columns 1 and 2 show the effect of robots and tools on employment and earnings of workers that have less education than a high-school diploma. Columns 3 and 4 show the effect on workers with a high-school diploma. Columns 5 and 6 show the effect on workers with at least some college education. Standard errors are clustered at the region–sector level.

Table B.27: Occupations, Robots, and Tools Control – Other Inputs

	(1) Δlog *Managers*	(2) Δlog *HS Professionals*	(3) Δlog *Technical Workers*	(4) Δlog *Adm Workers*	(5) Δlog *Operational Workers*
Δ log(Tools)	-0.0136	0.0081	0.1001***	0.0906***	0.2221***
	(0.0354)	(0.0531)	(0.0377)	(0.0289)	(0.0396)
Δ log(Robots)	0.0318	0.0184	-0.0283	-0.1043***	-0.1580***
	(0.0252)	(0.0356)	(0.0268)	(0.0264)	(0.0369)
N	44303	19525	69025	122064	132237
Year FE	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment of different occupations. Instead of using all machines, we limit the sample to machines that have text similarity to robot or tool above the median. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital,import of other inputs, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.28: Occupations, Robots, and Tools – Year Fixed Effects

	(1) Δlog *Managers*	(2) Δlog *HS Professionals*	(3) Δlog *Technical Workers*	(4) Δlog *Adm Workers*	(5) Δlog *Operational Workers*
Δ log(Tools)	0.0040	-0.0127	0.0375	0.0885***	0.1623***
	(0.0229)	(0.0294)	(0.0256)	(0.0217)	(0.0295)
Δ log(Robots)	0.0271**	0.0473***	0.0465***	-0.0485***	-0.0638***
	(0.0122)	(0.0166)	(0.0142)	(0.0135)	(0.0196)
N	46426	20292	72858	134134	149620
Year FE	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment of different occupational groups. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Standard errors are clustered at the region–sector level.

Table B.29: Occupations, Robots, and Tools – Year and Sector Fixed Effects

	(1) Δlog *Managers*	(2) Δlog *HS Professionals*	(3) Δlog *Technical Workers*	(4) Δlog *Adm Workers*	(5) Δlog *Operational Workers*
Δ log(Tools)	0.0148	0.0091	0.0928***	0.1142***	0.2425***
	(0.0274)	(0.0384)	(0.0308)	(0.0260)	(0.0364)
Δ log(Robots)	0.0146	0.0139	-0.0268	-0.1352***	-0.2035***
	(0.0232)	(0.0319)	(0.0259)	(0.0275)	(0.0405)
N	46425	20292	72858	134134	149620
Year FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment of different occupational groups. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.30: Occupations, Robots, and Tools – Market Fixed Effects

	(1) Δlog *Managers*	(2) Δlog *HS Professionals*	(3) Δlog *Technical Workers*	(4) Δlog *Adm Workers*	(5) Δlog *Operational Workers*
Δ log(Tools)	0.0072	0.0013	0.0851***	0.1243***	0.2333***
	(0.0273)	(0.0412)	(0.0294)	(0.0255)	(0.0342)
Δ log(Robots)	0.0175	0.0159	-0.0184	-0.1398***	-0.1855***
	(0.0230)	(0.0334)	(0.0250)	(0.0271)	(0.0384)
N	46405	20278	72802	134096	149596
Year FE	✓	✓	✓	✓	✓
Reg-Sec FE	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment of different occupations. Instead of using all machines, we limit the sample to machines that have text similarity to robot or tool above the median. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, and region-sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.31: Occupations, Robots, and Tools – Year × Initial Employment

	(1) Δlog *Managers*	(2) Δlog *HS Professionals*	(3) Δlog *Technical Workers*	(4) Δlog *Adm Workers*	(5) Δlog *Operational Workers*
Δ log(Tools)	0.0120	0.0079	0.0832***	0.1057***	0.2198***
	(0.0263)	(0.0385)	(0.0292)	(0.0242)	(0.0326)
Δ log(Robots)	0.0146	0.0175	-0.0185	-0.1267***	-0.1732***
	(0.0231)	(0.0328)	(0.0255)	(0.0271)	(0.0379)
N	46422	20288	72857	134132	149619
Year FE	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment of different occupations. Instead of using all machines, we limit the sample to machines that have text similarity to robot or tool above the median. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, sector fixed effects, and initial employment interacted with year. Standard errors are clustered at the region–sector level.

Table B.32: Occupations, Robots, and Tools Control – Year × Pre-period Growth

	(1) Δlog *Managers*	(2) Δlog *HS Professionals*	(3) Δlog *Technical Workers*	(4) Δlog *Adm Workers*	(5) Δlog *Operational Workers*
Δ log(Tools)	0.0242	0.0173	0.0750***	0.0831***	0.1888***
	(0.0260)	(0.0378)	(0.0285)	(0.0229)	(0.0305)
Δ log(Robots)	-0.0018	0.0041	-0.0239	-0.1105***	-0.1473***
	(0.0217)	(0.0302)	(0.0238)	(0.0249)	(0.0344)
N	46422	20288	72857	134132	149619
Year FE	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment of different occupations. Instead of using all machines, we limit the sample to machines that have text similarity to robot or tool above the median. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997 interacted with year, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

B.3.5 Higher Degree of Text Similarity

Table B.33: Effect of Tools and Robots on Employment When Limiting the Sample to High Text Similarity Machines

	(1) Δ log *Employment*	(2) Δ log *Earnings*	(3) Δ log *Wage Bill*	(5) Δ log *H.S. Drop.*	(6) Δ log *H.S. Complete*	(7) Δ log *College or More*
Δ log(Tools)	0.225***	0.0521***	0.277***	0.222***	0.102***	0.0536*
	(0.0322)	(0.00989)	(0.0373)	(0.0330)	(0.0339)	(0.0306)
Δ log(Robots)	-0.156***	-0.0452***	-0.201***	-0.183***	0.00572	0.00119
	(0.0294)	(0.00919)	(0.0341)	(0.0299)	(0.0268)	(0.0227)
N	204069	204069	204069	194269	116352	75878
Year FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on employment. Instead of using all machines, we limit the sample to machines that have text-similarity to robot or tool above the median. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. All specifications have year fixed effects. In column 1, there are no controls other than year fixed effects. Column 2 adds the baseline controls, i.e., growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Column 3 adds region FE to the baseline controls. Column 4 adds sector FE to the baseline controls. Column 5 includes as controls the baseline controls, region FE, and sector FE. Column 6 includes sector–region FEs and the baseline controls. Standard errors are clustered at the region–sector level.

Table B.34: Effect of Tools and Robots on Different Occupations When Limiting the Sample to High Text Similarity Machines

	(1) Δ*log* *Managers*	(2) Δ*log* *HS Professionals*	(3) Δ*log* *Technical Workers*	(4) Δ*log* *Adm Workers*	(5) Δ*log* *Operational Workers*
Δ log(Tools)	0.0135	0.0226	0.1116***	0.1448***	0.2993***
	(0.0320)	(0.0417)	(0.0356)	(0.0319)	(0.0469)
Δ log(Robots)	0.0284	0.0069	-0.0306	-0.0619**	-0.1784***
	(0.0215)	(0.0293)	(0.0244)	(0.0259)	(0.0374)
N	46422	20288	72857	134132	149619
Year FE	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (10) on labor market outcomes. Instead of using all machines, we limit the sample to machines that have text similarity to robot or tool above the median. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (12) and (13). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

C Appendix for Quantitative Model

C.1 Additional Equations

Firms. Consider a firm's choice of technology $l \in \{R, T\}$. Based on the properties of the Fréchet distribution and the firm's profit maximization, the expenditure share by firm i on tasks performed with technology l equals the following:

$$\pi_n^{s,l}(i) = \frac{T_n^{s,l}(i)(\Theta_n^{s,l})^{-\theta}}{(\Phi_n^s(i))^{-\theta}},$$

where $\Phi_n^s(i) = \left(\sum_{l=1}^{L} T_n^{s,l}(i)(\Theta_n^{s,l})^{-\theta}\right)^{-\frac{1}{\theta}}$ denotes the cost index of the value-added component of the firm's output. The price of the firm's value added is as follows: $p_n^{s,VA}(i) = \gamma\Phi_n^s(i)$. According to the firm's production function, Equation (16), and the firm's profit maximization, the firm's output price equals the following:

$$p_n^s(i) = \left[p_n^{s,VA}(i)\right]^{\gamma^s} \prod_{s'=1}^{S} \left[P_n^{s'}\right]^{\gamma^{ss'}}, \tag{C.1}$$

where $P_n^{s'}$ denotes the composite goods price in region n, sector s'.

Sectoral Production and Trade. Due to the constant return to scale and perfect competition, the output price index at the region–sector level (the price index associated with y_n^s) is determined by firm-level prices as follows:

$$[p_n^s]^{1-\phi} = \frac{1}{A_n^s}\left[\int_0^1 (p_n^s(i))^{1-\phi} di\right]^{1-\phi} \tag{C.2}$$

Sector s in region n has the following expenditure share on the output from region n':

$$\pi_{nn'}^s = \frac{(p_{n'}^s h_{nn'}^s t_{nn'}^s)^{1-\epsilon^s}}{(P_n^s)^{1-\epsilon^s}} \tag{C.3}$$

Capital Goods Sector. Using Equation (17), we observe that the production of investment goods decreases with the cost of capital production, $\Sigma_n^{s,l}$. Therefore, an increase in capital import tariffs can reduce investment:

$$I_n^{s,l} = \left(\frac{(1-\xi^l) P_n^{s,l}}{\Sigma_n^{s,l}} \right)^{\frac{1-\xi^l}{\xi^l}} . \tag{C.4}$$

Worker's Problem. Consider workers of type $e \in \{H, L\}$. Solving the worker's intratemporal problem, the time t utility equals the following:

$$u_{n,t}^{s,e} = \begin{cases} \frac{a_{n,t}^{s,e}(1-B) w_{n,t}^{s,e}}{P_{n,t}} & s \in \{1, ..., S\}, \\ \frac{a_{n,t}^{s,e}(1-B) b_n}{P_{n,t}} & s = S+1, \end{cases} \tag{C.5}$$

$$\text{where } P_n = \prod_{s=1}^{S} (P_n^s)^{\alpha^s} . \tag{C.6}$$

The probability that a type-e worker in region n, sector s will choose region n', sector s' in the next period equals the following:

$$s_{n'n,t}^{s's,e} = \frac{\exp(\lambda^e \beta v_{n',t+1}^{s',e} - \kappa_{n'n,t}^{s's,e})^{1/\rho^e}}{\sum_{n'=1}^{N} \sum_{s'=1}^{S+1} \exp(\lambda^e \beta v_{n',t+1}^{s',e} - \kappa_{n'n,t}^{s's,e})^{1/\rho^e}} . \tag{C.7}$$

Therefore, $1/\rho^e$ indicates the migration elasticity. It determines how easily workers of each type can switch sectors and locations based on their lifetime utility in the destination sector and location.

The following share of entrants will choose to become high-skilled:

$$\tilde{s}_{n,t}^{s,H} = \frac{\exp(\beta v_{n,t+1}^{s,H} - f^H)^{1/\tilde{\rho}}}{\exp(\beta v_{n,t+1}^{s,H} - f^H)^{1/\tilde{\rho}} + \exp(\beta v_{n,t+1}^{s,L})^{1/\tilde{\rho}}} , \tag{C.8}$$

where $1/\tilde{\rho}$ measures the skill choice elasticity.

According to the worker's problem, labor supply at the level of regions or sectors will follow the following law of motion:

$$l_{n',t+1}^{s',H} = \zeta^H \sum_{n=1}^{N} \sum_{s=1}^{S+1} s_{n'n,t}^{s's,H} l_{n,t}^{s,H} + \left((1-\zeta^H) l_{n,t}^{s,H} + (1-\zeta^L) l_{n,t}^{s,L} \right) \tilde{s}_{n,t}^{s,L} , \tag{C.9}$$

and

$$l_{n',t+1}^{s',L} = \zeta^L \sum_{n=1}^{N} \sum_{s=1}^{S+1} s_{n'n,t}^{s's,L} l_{n,t}^{s,L} + \left((1-\zeta^H) l_{n,t}^{s,H} + (1-\zeta^L) l_{n,t}^{s,L} \right) \tilde{s}_{n,t}^{s,L}. \tag{C.10}$$

C.1.1 Market-Clearing Conditions

Robot Capital. The market-clearing condition for robot capital at the region–sector level is the following:

$$R_n^{s,R} K_n^{s,R} = \int_{i=0}^{1} \frac{T^{s,R}(i)(R_n^{s,R})^{-\theta}}{(\Phi_n^s(i))^{-\theta}} \frac{(p_n^s(i))^{-\phi}}{(p_n^s)^{-\phi}} \gamma^s p_n^s Y_n^s di, \tag{C.11}$$

where $\frac{(p_n^s(i))^{-\phi}}{(p_n^s)^{-\phi}} \gamma^s p_n^s Y_n^s$ refers to firm i's value added and $\frac{T^{s,R}(i)(R_n^{s,R})^{-\theta}}{(\Phi_n^s(i))^{-\theta}}$ is the share of robot capital in the firm's value added. Integrating all firms in this region–sector, we get the total demand for the robot capital, which is equal to the supply of capital.

Tool Capital. Similarly, the market-clearing condition for tool capital is the following:

$$R_n^{s,T} K_n^{s,T}(i) = \int_{i=0}^{1} (1-\delta) \frac{\left(\left(\left[w_n^{s,L} \right]^{\delta} \left[R_n^{s,T} \right]^{1-\delta} \right) \right)^{1-\sigma}}{(\Theta_n^{s,T}(i))^{1-\sigma}} \frac{(\Theta_n^{s,T}(i))^{-\theta}}{(\Phi_n^s(i))^{-\theta}} \frac{(p_n^s(i))^{-\phi}}{(p_n^s)^{-\phi}} \gamma^s p_n^s Y_n^s di. \tag{C.12}$$

High-skilled Workers. The market-clearing condition for high-skilled workers is the following:

$$w_n^{s,H} l_n^{s,H} = \int_{i=0}^{1} \frac{A^{s,T}(i)(w_n^{s,H})^{1-\sigma}}{(\Theta_n^{s,T}(i))^{1-\sigma}} \frac{(\Theta_n^{s,T}(i))^{-\theta}}{(\Phi_n^s(i))^{-\theta}} \frac{(p_n^s(i))^{-\phi}}{(p_n^s)^{-\phi}} \gamma^s p_n^s Y_n^s di. \tag{C.13}$$

Low-skilled Workers The market-clearing condition for low-skilled workers is the following:

$$w_n^{s,L} l_n^{s,L} = \int_{i=0}^{1} \delta \frac{\left(\left[w_n^{s,L} \right]^{\delta} \left[R_n^{s,T} \right]^{1-\delta} \right)^{1-\sigma}}{(\Theta_n^{s,T}(i))^{1-\sigma}} \frac{(\Theta_n^{s,T}(i))^{-\theta}}{(\Phi_n^s(i))^{-\theta}} \frac{(p_n^s(i))^{-\phi}}{(p_n^s)^{-\phi}} \gamma^s p_n^s Y_n^s di. \tag{C.14}$$

Composite Goods. Composite goods are consumed and used as production inputs. Therefore, their market-clearing condition is the following:

$$X_n^s = \underbrace{P_n^s C_n^s}_{\text{Consumption}} + \sum_{s'=1}^{S} \gamma^{s's} (\underbrace{\sum_{n'=1}^{N} X_{n'}^{s'} \pi_{n'n}^{s'}}_{\text{Sector } s' \text{ domestic sales}} + \underbrace{EF_n^{s'} (p_n^{s'})^{1-\sigma^{s'}}}_{\text{Sector } s' \text{ exports}}), \tag{C.15}$$

where EF_n^s, an exogenous parameter, governs the size of the foreign demand. Regional consumption of sectoral composite goods equals the following:

$$P_n^s C_n^s = \alpha^s \left(\sum_{s=1}^{S} (w_n^{s,H} l_n^{s,H} + w_n^{s,L} l_n^{s,L} + R_n^{s,R} K_n^{s,R} + R_n^{s,T} K_n^{s,T}) + TDG_n \right), \tag{C.16}$$

where TDG_n denotes the trade deficit and the tariff revenue in the composite goods sectors and equals the following:

$$TDG_n = \sum_{s=1}^{S} (X_n^s \pi_{nN+1}^s - EF_n^s (p_n^s)^{1-\sigma^s}). \tag{C.17}$$

Region n, sector s output is used both for domestic expenditure and for exports. Therefore, its market-clearing condition is the following:

$$p_n^s Y_n^s = \underbrace{\sum_{n'=1}^{N} X_{n'}^s \pi_{n'n}^s}_{\text{Domestic sales}} + \underbrace{EF_n^s (p_n^s)^{1-\sigma^s}}_{\text{Exports}}. \tag{C.18}$$

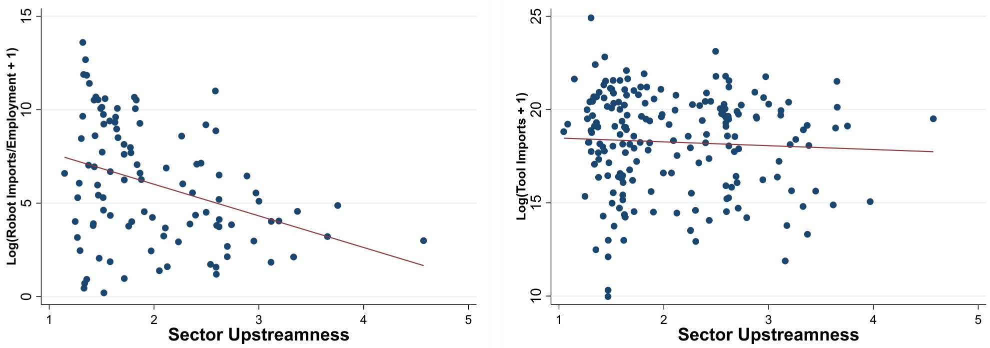
The foreign transfer equals the trade deficit due to trade in composite goods and imported capital goods:

$$TD_n = TDG_n + \sum_{s=1}^{S} \left(\Sigma_n^{s,T} M_n^{s,T} \frac{\left[h_{nN+1}^{s,T} t_{N+1}^{s,T} \right]^{1-\sigma^T}}{\left[\Sigma_n^{s,T} \right]^{1-\sigma^T}} + \Sigma_n^{s,R} M_n^{s,R} \frac{\left[h_{nN+1}^{s,R} t_{N+1}^{s,R} \right]^{1-\sigma^R}}{\left[\Sigma_n^{s,R} \right]^{1-\sigma^R}} \right). \tag{C.19}$$

Equilibrium. The equilibrium is defined as a set of prices $\left\{ w_n^{s,H}, w_n^{s,L}, R_n^{s,R}, R_n^{s,T}, p_n^s, P_n^s, b \right\}$, such that workers' value functions follow Equation (20), sector–region and skill choice prob-

Figure C.1: Robots, Tools, and Sector Upstreamness

(a) Robot Imports and Sector Upstreamness (b) Tool Imports and Sector Upstreamness



Description: This figure shows the estimated coefficients of model B.2 on employment and average wage of firms adopting labor-augmenting machines. For each firm importing a labor-augmenting machine, we create a control firm that matches in terms of employment, share of high-school dropouts, age, and sector in the three years before the adoption of the machine. The sample is from 1997 to 2015. Standard errors are clustered at the firm level.

abilities follow Equations (C.7) and (C.8), the supply of labor follows Equations (C.9) and (C.10), the supply of capital follows Problem (18), and market-clearing conditions (C.11)–(C.15) and (22) hold.[57]

C.2 Parameterization

Firm-level Productivity We assume that the firm-level high-skilled worker-augmenting productivity, $A^{s,T}_{n,t}(i)$, and robot-augmenting productivity, $T^{s,R}_{n,t}(i)$, follow joint log-normal distributions. They are independent across regions, sectors, firms, and time, but are correlated within a firm. The reason for this within-firm correlation is that the high-tech firms that are better at utilizing robots may also be better at utilizing high-skilled workers. Assume that $A^{s,T}(i) = \exp(\mu^s_1 + \sigma^s_1 Z^s_1(i))$ and $T^{s,R}(i) = \exp(\mu^s_2 + \sigma^s_2 Z^s_2(i))$ and that $Z^s_1(i)$ and $Z^s_2(i)$ are random variables that follow a bi-variate normal distribution:[58]

$$\begin{pmatrix} Z^s_1 \\ Z^s_2 \end{pmatrix} = \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho^s \\ \rho^s & 1 \end{pmatrix}\right). \tag{C.20}$$

[57]Since we focus on steady state-to-steady state changes, we omit the time dimension from the prices under consideration.

[58]We assume that these parameters depend on the sector instead of the region, since they govern the relative importance of high-skilled workers and robots in the technology of production. Therefore, they are more likely to be affected by the sector for which the technologies are developed than by the location in which they are used.

The average high-skilled worker and robot productivity μ_1^s and μ_2^s, their standard deviations σ_1^s and σ_2^s, and the correlation ρ^s are the parameters we will estimate.

Trade and Migration Costs We assume that the domestic trade cost follows Equation (C.21). The trade cost from region n' to region n is a function of several factors: (1) whether the origin is identical to the destination, (2) whether the two regions share a border, (3) the distance between the two regions, (4) the proximity of the origin and destination to the nearest coast, and (5) the number of ports present in the origin and destination. Additionally, trade cost depends on the sector of the traded products. We consider two measures of sector heterogeneity that may influence trade costs: (1) the degree of a sector's upstream position and (2) the share of high-skilled workers in sectoral employment. These sectoral variables, along with their interactions with the geographical variables mentioned above, affect trade costs.

$$
\begin{aligned}
\log(h^s_{nn'}) = {} & \beta^0 \mathbf{1}(n'=n) + \beta^1 \text{Contig}_{n'n} + \beta^2 \log(\text{Dist to Coast}_n) + \beta^3 \log(\text{Dist to Coast}_{n'}) \\
& + \beta^4 \mathbb{N}(\text{Ports})_n + \beta^5 \mathbb{N}(\text{Ports})_{n'} + \beta^6 \log(\text{Dist}_{n'n}) + \beta^7 \text{Contig}_{n'n} \log(\text{U}^s) \\
& + \beta^8 \log(\text{Dist to Coast}_n) \log(\text{U}^s) + \beta^9 \log(\text{Dist to Coast}_{n'}) \log(\text{U}^s) \\
& + \beta^{10} \mathbb{N}(\text{Ports})_n \log(\text{U}^s) + \beta^{11} \mathbb{N}(\text{Ports})_{n'} \log(\text{U}^s) + \beta^{12} \log(\text{Dist}_{n'n}) \log(\text{U}^s) \\
& + \beta^{13} \mathbf{1}(n'=n) \log(\text{U}^s) + \beta^{14} \log(\text{U}^s) + \beta^{15} \mathbf{1}(n'=n) \log(\text{high-skilled labor share}^s) + \beta^{16} \text{Contig}_{n'n} \log(\text{high-skilled labor share}^s) \\
& + \beta^{17} \log(\text{Dist to Coast}_n) \log(\text{high-skilled labor share}^s) + \beta^{18} \log(\text{Dist to Coast}_{n'}) \log(\text{high-skilled labor share}^s) \\
& + \beta^{19} \mathbb{N}(\text{Ports})_n \log(\text{high-skilled labor share}^s) + \beta^{20} \mathbb{N}(\text{Ports})_{n'} \log(\text{high-skilled labor share}^s) + \beta^{21} \log(\text{high-skilled labor share}^s) \\
& + \beta^{22} \log(\text{Dist}_{n'n}) \log(\text{high-skilled labor share}^s). \qquad \text{(C.21)}
\end{aligned}
$$

We assume that the non-tariff trade barrier faced by a region–sector when importing composite goods (Equation (C.22)), as well as robot (Equation (C.23)) and tool capital (Equation (C.24)), depends on several factors: (1) the distance to the coast, (2) the number of ports in the region, (3) the sector's upstreamness, and (4) the sector's high-skilled employment share. Additionally, the interactions between geographical and sectoral variables are taken into account. Moreover, an intercept term is included to account for the home bias against imports.

$$\log(h^s_{nN+1}) = \beta^{23}\log(\text{Dist to Coast}_n) + \beta^{24}\mathbb{N}(\text{Ports})_n + \beta^{25}\log(\text{Dist to Coast}_n)\log(\text{U}^s) + \beta^{26}\mathbb{N}(\text{Ports})_n\log(\text{U}^s) + \beta^{27}\log(\text{U}^s)$$
$$+ \beta^{28} + \beta^{29}\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s) + \beta^{30}\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$$
$$+ \beta^{31}\log(\text{high-skilled labor share}^s). \tag{C.22}$$

$$\log(h^{s,R}_{nN+1}) = \beta^{1,R}\log(\text{Dist to Coast}_n) + \beta^{2,R}\mathbb{N}(\text{Ports})_n + \beta^{3,R}\log(\text{Dist to Coast}_{n'})\log(\text{U}^s) + \beta^{4,R}\mathbb{N}(\text{Ports})_{n'}\log(\text{U}^s) + \beta^{5,R}\log(\text{U}^s)$$
$$+ \beta^{6,R} + \beta^{7,R}\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s) + \beta^{8,R}\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$$
$$+ \beta^{9,R}\log(\text{high-skilled labor share}^s). \tag{C.23}$$

$$\log(h^{s,T}_{nN+1}) = \beta^{1,T}\log(\text{Dist to Coast}_n) + \beta^{2,T}\mathbb{N}(\text{Ports})_n + \beta^{3,T}\log(\text{Dist to Coast}_{n'})\log(\text{U}^s) + \beta^{4,T}\mathbb{N}(\text{Ports})_{n'}\log(\text{U}^s) + \beta^{5,T}\log(\text{U}^s)$$
$$+ \beta^{6,T} + \beta^{7,T}\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s) + \beta^{8,T}\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$$
$$+ \beta^{9,T}\log(\text{high-skilled labor share}^s). \tag{C.24}$$

The migration cost depends on the migration origin region–sector and the migration destination region–sector. We assume that the migration cost is a function of the same geographical variables that affect the domestic trade cost. In addition, they are also influenced by the absolute values of the difference between the upstreamness and the high-skilled labor shares of the origin sector and the destination sector. We also include in the migration cost the interactions between the geographical distances and the sectoral differences. The migration cost is parameterized as follows:

$$\log(\kappa^{s's}_{n'n}) = \chi^0\mathbf{1}(n'=n) + \chi^1\text{Contig}_{n'n} + \chi^2\log(\text{Dist}_{n'n}) + \chi^3|\log(\text{U}^{s'}) - \log(\text{U}^s)| + \chi^4\text{Contig}_{n'n}|\log(\text{U}^{s'}) - \log(\text{U}^s)|$$
$$+ \chi^5\log(\text{Dist}_{n'n})|\log(\text{U}^{s'}) - \log(\text{U}^s)| + \chi^6\mathbf{1}(n'=n)|\log(\text{U}^{s'}) - \log(\text{U}^s)| + \chi^7|\text{high-skilled labor share}^{s'} - \text{high-skilled labor share}^s|$$
$$+ \chi^8\text{Contig}_{n'n}|\text{high-skilled labor share}^{s'} - \text{high-skilled labor share}^s|$$
$$+ \chi^9\log(\text{Dist}_{n'n})|\text{high-skilled labor share}^{s'} - \text{high-skilled labor share}^s|$$
$$+ \chi^{10}\mathbf{1}(n'=n)|\text{high-skilled labor share}^{s'} - \text{high-skilled labor share}^s|. \tag{C.25}$$

C.3 Estimation

In the first step, we calibrate a set of parameters outside the model. Table C.3 summarizes these parameters.

Trade Elasticities We calibrate sectoral trade elasticities for the composite goods to the estimates acquired in De Souza and Li (2022).[59] Using a specification similar to the one developed in Section 5, we estimate robot and tool capital trade elasticities to 5.64 and 3.11, respectively.

We estimate the trade elasticity of different types of capital goods by studying how tariff changes affect changes in imports at the regional and sectoral levels.[60] For robots:

$$\Delta \log \left(Import^{R}_{is,t} \right) = \theta^{R} \Delta \log \left(tariff^{R}_{s,t} \right) + Fixed\ effect_i + Fixed\ effect_s + Fixed\ effect_t + \epsilon_{ist}, \tag{C.26}$$

where $\Delta \log(Import^{R}_{is,t})$ is the log change in robot imports in region i, sector s, from year $t-5$ to year t. $\log(tariff^{R}_{s,t})$ is the log change in a weighted average[61] tariff on robots in region i, sector s, from year $t-5$ to year t. θ^{R} is the trade elasticity for robots. Similarly, we estimate the following for tools:

$$\Delta \log \left(Import^{T}_{is,t} \right) = \theta^{R} \Delta \log \left(tariff^{T}_{s,t} \right) + Fixed\ effect_i + Fixed\ effect_s + Fixed\ effect_t + \epsilon_{is}, \tag{C.27}$$

where θ^{T} is the trade elasticity for tools. Table C.1 shows the parameters estimated based on Equations (C.26) and (C.27), along with other robustness tests. Estimators from the main specification (column 2) suggest the elasticities of $\theta^{R} = -5.64$ and $\theta^{T} = -3.11$.[62]

[59] In De Souza and Li (2022), we utilize anti-dumping investigations and anti-dumping tariffs and a difference-in-differences strategy to study the effect of tariffs. We use the products and sectors that are investigated for dumping but do not receive tariff protection as the control group.

[60] We leverage variations across both regions and sectors to increase statistical power. Different regions import distinct capital goods, resulting in varying tariffs when measured using sector-level weighted averages.

[61] We calculate the average tariff on robot products using product-level import value as weight.

[62] This implies that $\epsilon^{R} = 1 - \theta^{R} = 6.64$ and $\epsilon^{T} = 1 - \theta^{T} = 4.11$.

Table C.1: **Trade Elasticity of Capital Goods**

	Measured by 5-Year Change			Measured by 1-Year Change		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Trade Elasticity of Robots						
θ^R	-19.58***	-5.637***	-6.079***	-1.932***	-1.940***	-2.001***
	(2.477)	(1.391)	(1.465)	(0.440)	(0.529)	(0.517)
Observation	325271	325271	325271	400501	400501	400501
R^2	0.029	0.220	0.221	0.000	0.009	0.009
Year FE	N	Y	Y	N	Y	Y
Sector FE	N	Y	Y	N	Y	Y
Region FE	N	Y	Y	N	Y	Y
Control	N	N	Y	N	N	Y
	(7)	(8)	(9)	(10)	(11)	(12)
Panel B. Trade Elasticity of Tools						
θ^T	-12.64***	-3.108*	-3.815**	-1.473***	-4.702***	-4.572***
	(1.242)	(1.684)	(1.863)	(0.207)	(0.667)	(0.658)
Observation	325271	325271	325271	400501	400501	400501
R^2	0.009	0.348	0.349	0.000	0.013	0.013
Year FE	N	Y	Y	N	Y	Y
Sector FE	N	Y	Y	N	Y	Y
Region FE	N	Y	Y	N	Y	Y
Control	N	N	Y	N	N	Y

Description: This table presents trade elasticities estimated from Equations (C.26) and (C.27). θ^R is the trade elasticity of labor-saving capital goods. θ^T is the trade elasticity of labor-augmenting capital goods. Controls include the tariff change on sectoral output and input. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Migration Elasticities We apply the method used by Artuç et al. (2010), Dix-Carneiro (2014), and Caliendo et al. (2019) to estimate the migration elasticities for both skill types. Manipulating Equation (C.7), we can express migration shares as a function of wages and migration shares in the next period, and the coefficient in front of wages indicates the the migration elasticity. We conduct an instrumental variable regression using lagged wages as the instrument for the next period's wages in order to identify the coefficient. We estimate the migration elasticity (the inverse of ρ^e, $e \in \{1, 2\}$) to be 0.167 for high-skilled workers and 0.141 for low-skilled workers. These estimates are consistent with our intuition that high-skilled workers should be more mobile than low-skilled workers. In studies using US state–sector level migration data, Artuç et al. (2010) found a migration elasticity of 0.532 and Caliendo et al. (2019) found a migration elasticity of 0.495. We estimate lower mobility rates based on Brazilian data, which is in accordance with our intuition that population mobility is lower in developing countries than in advanced economies.

With Equation (C.7), the log difference between the probability of migrating from region n-sector j to region i-sector k and the probability of staying in region n-sector j is the following:

$$\log(s^{kj,e}_{in,t}) - \log(s^{jj,e}_{nn,t}) = \frac{\zeta^e\beta}{\rho^e} v^{k,e}_{i,t+1} - \frac{\zeta^e\beta}{\rho^e} v^{j,e}_{n,t+1} - \frac{1}{\rho^e}.\kappa^{kj,e}_{in,t}. \tag{C.28}$$

Use Equation (20) to substitute the value functions:

$$\begin{aligned}\log(s^{kj,e}_{in,t}) - \log(s^{jj,e}_{nn,t}) = \frac{\zeta^e\beta}{\rho^e} \Bigg(&\log(a^{k,e}_{i,t+1}) + \log(\frac{w^{k,e}_{i,t+1}}{P_{i,t+1}}) + \rho^e \log(\sum_{n'=1}^{N}\sum_{s'=1}^{S+1} \exp(\zeta^e\beta v^{s',e}_{n',t+2} - \kappa^{s'k,e}_{n'i,t+1})^{1/\rho^e}) \\ &- \log(a^{j,e}_{n,t+1}) - \log(\frac{w^{j,e}_{n,t+1}}{P_{n,t+1}}) - \rho^e \log(\sum_{n'=1}^{N}\sum_{s'=1}^{S+1} \exp(\zeta^e\beta v^{s',e}_{n',t+1} - \kappa^{s'j,e}_{n'n,t})^{1/\rho^e})\Bigg) - \frac{1}{\rho^e}\kappa^{kj,e}_{in,t}.\end{aligned} \tag{C.29}$$

To substitute the region–sector–level expected value, use Equation (C.7) again at time $t+1$:

$$\begin{aligned}\log(s^{kj,e}_{in,t+1}) - \log(s^{kk,e}_{ii,t+1}) = &-\frac{1}{\rho^e}\kappa^{kj,e}_{in,t+1} - \log(\sum_{n'=1}^{N}\sum_{s'=1}^{S+1} \exp(\zeta^e\beta v^{s',e}_{n',t+2} - \kappa^{s'j,e}_{n'n,t+2})^{1/\rho^e}) \\ &+ \log(\sum_{n'=1}^{N}\sum_{s'=1}^{S+1} \exp(\zeta^e\beta v^{s',e}_{n',t+2} - \kappa^{s'k,e}_{n'i,t+2})^{1/\rho^e}).\end{aligned} \tag{C.30}$$

Plug Equation (C.30) into Equation (C.29):

$$\begin{aligned}\log(s^{kj,e}_{in,t}) - \log(s^{jj,e}_{nn,t}) = &\frac{\zeta^e\beta}{\rho^e}\left(\log(\frac{w^{k,e}_{i,t+1}}{P_{i,t+1}}) - \log(\frac{w^{j,e}_{n,t+1}}{P_{n,t+1}})\right) + \zeta^e\beta\left(\log(s^{kj,e}_{in,t+1}) - \log(s^{kk,e}_{ii,t+1})\right) \\ &+ \frac{\zeta^e\beta}{\rho^e}\kappa^{kj,e}_{in,t+1} - \frac{1}{\rho^e}\kappa^{kj,e}_{in,t} + \frac{\zeta^e\beta}{\rho^e}\left(\log(a^{k,e}_{i,t+1}) - \log(a^{j,e}_{n,t+1})\right).\end{aligned} \tag{C.31}$$

Accordingly, our estimation equation will be:

$$\log(s^{kj,e}_{in,t}) - \log(s^{jj,e}_{nn,t}) - \zeta^e\beta(\log(s^{kj,e}_{in,t+1}) - \log(s^{kk,e}_{ii,t+1})) = \frac{\zeta^e\beta}{\rho^e}(\log(w^{k,e}_{i,t+1}) - \log(w^{j,e}_{n,t+1})) + \phi_{i,t} + \phi_{n,t} + \epsilon^{kj,e}_{in,t}. \tag{C.32}$$

This amounts to regressing the log difference between the probability of mitigating from region n-sector j to region i-sector k and the probability of remaining in region n-sector j. This is adjusted by the log difference between the probability of mitigating from region n-sector j to region i-sector k and the probability of staying in region i-sector k during the subsequent period. The dependent variable is the log difference in wages between region i-sector k and region n-sector j. Fixed effect controls are included to address the region-level price indices. Since the continuation probability for each worker type, ζ^e, and the discount factor, β, are both known, the inverse of the migration probability, ρ^e, can be obtained from the estimated coefficient.

Comparing Equations (C.31) and (C.32), the error term, $\epsilon_{in,t}^{kj,e}$, absorbs migration costs and region–sector level amenities. To address potential bias, similar to Caliendo et al. (2019), we use past wages (in $t-1$) as instruments for the wages in $t+1$.[63] The identifying assumption is that past wages are uncorrelated with current and future migration costs and future amenities.

Table C.2: **Migration Elasticity and Skill Choice Elasticity**

	Migration Elasticity				Skill Choice Elasticity	
	$\frac{1}{\rho^H}$		$\frac{1}{\rho^L}$		$\frac{1}{\tilde{\rho}}$	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Parameters	0.141***	0.167***	0.131***	0.141***	0.022***	0.076***
	(0.005)	(0.006)	(0.008)	(0.010)	(0.0004)	(0.018)
Observation	255,321	251,838	345,991	344,822	94,836	94,089
Origin–Year FE	Y	Y	Y	Y	Y	Y
Destination–Year FE	Y	Y	Y	Y	Y	Y
R^2	0.109	0.003	0.136	0.001	0.197	-0.202
First stage F-statistic		257.42		164.50		20.46

Description: This table presents migration elasticities and skill choice elasticities estimated from Equations (C.32) and (C.36). ρ^H is the inverse of the migration elasticity of high-skilled workers. ρ^L is the inverse of the migration elasticity of low-skilled workers. $\tilde{\rho}$ is the skill choice elasticity. 2SLS specifications use wages in the previous period as instruments. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Columns (1)-(4) of Table C.2 show the parameters estimated from Equation (C.32). The 2SLS estimators imply migration elasticities of $\frac{1}{\rho^H} = 0.167$ and $\frac{1}{\rho^L} = 0.141$.

[63]Similar to Artuç et al. (2010) and Caliendo et al. (2019), we use $(\log(w_{i,t-1}^{k,e}) - \log(w_{n,t-1}^{j,e}))$ to instrument for $(\log(w_{i,t+1}^{k,e}) - \log(w_{n,t+1}^{j,e}))$.

Skill Choice Elasticity Using a similar approach, we estimate the skill choice elasticity of entrants, referred to as those entering the Brazilian matched employer–employee data for the first time. Equation (C.33) demonstrates that the share of new workers in a region–sector choosing to become high-skilled depends on the relative value functions of high-skilled and low-skilled workers. Equation (C.36) enables the value functions to be inverted and rewritten as migration shares, forming our estimation equation. We use lagged wages as instruments for migration shares.

We estimate the skill choice elasticity for new workers as follows. Compute the log difference between the probabilities of becoming a high-skilled versus a low-skilled worker in region n-sector s and in region n'-sector s'. Take the log difference between the two region-sectors and plug it into Equation (C.8):

$$\begin{aligned}&\Big(\log(\tilde{s}^{s,H}_{n,t}) - \log(\tilde{s}^{s,L}_{n,t})\Big) - \Big(\log(\tilde{s}^{s',H}_{n',t}) - \log(\tilde{s}^{s',L}_{n',t})\Big)\\ =&\frac{\beta}{\tilde{\rho}}(v^{s,H}_{n,t+1} - v^{s',H}_{n',t+1}) - \frac{\beta}{\tilde{\rho}}(v^{s,L}_{n,t+1} - v^{s',L}_{n',t+1})\end{aligned} \tag{C.33}$$

With Equation (C.7), we can express the value functions as migration shares and migration costs:

$$v^{s,e}_{n,t+1} - v^{s',e}_{n',t+1} = \frac{\rho^e}{\zeta^e \beta}\Big(\log(s^{ss,e}_{nn,t}) - \log(s^{s's,e}_{n'n,t})\Big) - \frac{1}{\zeta^e \beta}\kappa^{s's,e}_{n'n,t}, e \in \{1,2\}. \tag{C.34}$$

Plug Equation (C.34) into Equation (C.33):

$$\begin{aligned}&\Big(\log(\tilde{s}^{s,H}_{n,t}) - \log(\tilde{s}^{s,L}_{n,t})\Big) - \Big(\log(\tilde{s}^{s',H}_{n',t}) - \log(\tilde{s}^{s',L}_{n',t})\Big)\\ =&\frac{1}{\tilde{\rho}}\left[\frac{\rho^H}{\zeta^H}\Big(\log(s^{ss,H}_{nn,t}) - \log(s^{s's,H}_{n'n,t})\Big) - \frac{\rho^L}{\zeta^L}\Big(\log(s^{ss,L}_{nn,t}) - \log(s^{s's,L}_{n'n,t})\Big)\right] - (\frac{1}{\zeta^H}\kappa^{s's,H}_{n'n,t} - \frac{1}{\zeta^L}\kappa^{s's,L}_{n'n,t}).\end{aligned} \tag{C.35}$$

Equation (C.35) leads to our estimation equation:

$$
\begin{aligned}
&\left(\log(\tilde{s}^{s,H}_{n,t}) - \log(\tilde{s}^{s,L}_{n,t})\right) - \left(\log(\tilde{s}^{s',H}_{n',t}) - \log(\tilde{s}^{s',L}_{n',t})\right) \\
=&\frac{1}{\tilde{\rho}}\left[\frac{\rho^H}{\zeta^H}\left(\log(s^{ss,H}_{nn,t}) - \log(s^{s's,H}_{n'n,t})\right) - \frac{\rho^L}{\zeta^L}\left(\log(s^{ss,L}_{nn,t}) - \log(s^{s's,L}_{n'n,t})\right)\right] + \epsilon^{ss'}_{nn',t}. \qquad (C.36)
\end{aligned}
$$

Similar to the estimation of migration elasticities, we use wages at $t-1$ as instruments.[64] The identifying assumption is that past wages are uncorrelated with current migration costs.

Columns (5)-(6) of Table C.2 show the parameters estimated from Equation (C.36). The 2SLS estimator implies a skill choice elasticity of $\frac{1}{\tilde{\rho}} = 0.076$.

Other Parameters Calibrated Outside the Model Using the Brazilian matched employer–employee data, we calibrate workers' exit rates by type. In order to measure exit rates, we calculate, for an average year, the percentage of each type of worker who leaves the labor market and never returns. We calibrate the input-output coefficients, final consumption shares, and social insurance tax rates based on the values obtained in De Souza and Li (2022).

Table C.3: **Parameters Calibrated outside the Model**

Parameters			Targeted Moments
Variable	Var. Name	Value	Source
ϵ^s	Sectoral trade elasticities	3.7199 (mean)	De Souza and Li (2022)
ϵ^T	Tool capital goods trade elasticity	4.11	Estimated
ϵ^R	Robot capital goods trade elasticity	6.64	Estimated
ρ^H	Migration elasticity of high-skilled workers (inverse)	5.99	Estimated
ρ^L	Migration elasticity of low-skilled workers (inverse)	7.09	Estimated
$\tilde{\rho}$	Skill choice elasticity (inverse)	13.16	Estimated
ζ^H	Exit rate of high-skilled workers	0.035	Data
ζ^L	Exit rate of low-skilled workers	0.061	Data
$\gamma^{ss'}$	Input-output coefficient	Varies	De Souza and Li (2022)
α^s	Final consumption share	Varies	De Souza and Li (2022)
B	Social insurance tax rate	10.3%	"Government transfer rate" ("Renda de transferências governamentais") in the IPEA's database
β	Discount factor	0.96	Numerous

Description: This table presents model parameters that are externally calibrated.

C.4 Estimation

We estimate the remaining parameters using the Simulated Method of Moments (SMM), dividing them into two groups: cross-sectional and dynamic moments. We treat the Brazilian economy in 1997 as the initial steady state (t_0). The cross-sectional moments govern the economy's static aspects, while dynamic moments dictate its response to shocks (change

[64] The instruments are $[\log(w^{k,H}_{i,t-1}) - \log(w^{j,H}_{n,t-1}) - (\log(w^{k,L}_{i,t-1}) - \log(w^{j,L}_{n,t-1})]$.

from t_0 to t_1). To estimate parameters governing cross-sectional moments, we target Brazilian trade, employment, and migration in 1997 using the model's initial steady state. For dynamic moments, we replicate the empirical analysis in Section 5 using simulated data, searching for parameters related to production technologies involving robots or tools, namely $\{\theta, \phi, \sigma, \delta\}$ (elasticity of substitution between robots and tools, elasticity of substitution across firms, elasticity of substitution between high-skilled workers and the low-skilled-worker-tool bundle, and low-skilled workers' share in the low-skilled-worker-tool bundle). We use these four parameters to target four key empirical results – the impact of robot and tool imports on high-skilled and low-skilled employment – by replicating the instrumental variables(IV) regression with model simulated data, reflecting the change from initial to final steady states. In the SMM algorithm, we minimize the sum of squared differences between data moments and model counterparts, treating all moments with equal weight.

In particular, we estimate the trade cost-related parameters described in Section C.2 by targeting region–sector imports of robots, tools, and non-capital goods. In order to estimate migration cost-related parameters, we target migration shares from one region–sector to another. In order to estimate region–sector level productivity, we target the wage and employment of high-skilled and low-skilled workers by region and sector. To estimate the fixed cost of becoming a high-skilled worker, we target the annual average share of high-skilled workers among entrants.

We estimate the four key parameters – $\{\theta, \phi, \sigma, \delta\}$ – governing robot and tool technologies, which determine the impact of their capital imports on high-skilled and low-skilled employment. We target coefficients summarizing these effects, as presented in Section 6, and consider the following regression:[65]

$$\Delta \log(l_n^{s,e}) = \theta^{R,e} \Delta \log(robots_n^s) + \theta^{T,e} \Delta \log(tool_n^s) + \epsilon_n^{s,e}, e \in \{H, L\}, \tag{C.37}$$

where changes from the initial steady state to the final steady state in type-e employment,

[65] In the empirical counterpart of this regression in Section 5, we include additional controls, such as fixed effects for regions and sectors, output tariffs, other input tariffs, and pre-period growth. According to the data, these control variables are necessary because a number of shocks have affected both the labor market and the import of machinery. Model simulated data, however, do not contain such shocks, so we do not include additional controls in these regressions.

robot capital goods imports, and tool capital goods imports are represented by $\Delta \log(l_n^{s,e})$, $\Delta \log(robots_n^s)$, and $\Delta \log(tool_n^s)$, respectively.

Similar to the section 5, we use the exposures to robot and tool capital goods tariff changes as instruments for the changes in imports. As a measure of routine task shares in the model, we use the share of low-skilled workers and tools in region–sector value added in the initial steady state. Therefore, the instruments constructed with model-simulated data are the following:

$$\Delta IV_n^{s,R} = \frac{w_{n,t_0}^{s,L} l_{n,t_0}^{s,L} + R_{n,t_0}^{s,T} K_{n,t_0}^{s,T}}{\gamma^s p_{n,t_0}^s y_{n,t_0}^s} \Delta\tau^{s,R} \tag{C.38}$$

for robots, and

$$\Delta IV_n^{s,T} = (1 - \frac{w_{n,t_0}^{s,L} l_{n,t_0}^{s,L} + R_{n,t_0}^{s,T} K_{n,t_0}^{s,T}}{\gamma^s p_{n,t_0}^s y_{n,t_0}^s}) \Delta\tau^{s,T} \tag{C.39}$$

for tools.

We employ the Mathematical Programming with Equilibrium Constraints (MPEC) algorithm (Su and Judd 2012) to solve the model, incorporating both initial and final steady states in the constraints. This method enables us to solve for initial and final steady states, the changes across steady states listed in Equations (C.37), (C.38), and (C.39), and the IV regression coefficients per Equation (C.37). We then compute model moments and include them in the objective function along with data moments.

C.5 Estimation Results and Model Fit

Table 6 displays the estimated values of the key parameters that govern robot and tool technologies. Table C.5 presents the estimates of other parameters. As anticipated, more distant regions experience higher domestic trade costs. Upstream and low-skilled sectors also incur higher trade costs. In terms of import costs, greater distance increases the cost of importing sectoral goods, robot capital goods, and tool capital goods. Having more ports significantly reduces import costs. A home bias exists against importing all goods. Migration costs rise with the distance between regions and the differences in sector upstreamness and skill levels between origin and destination sectors. Furthermore, becoming a high-skilled worker incurs a fixed cost equivalent to 7.8 years of average high-skilled wages.

Table C.4 shows that we precisely match the key empirical moments with the four robot and tool technology parameters.

Table C.4: **Match of Key Moments**

Data Moments			Model Moments
Variable	Var. Name	Value	Value
$\theta^{R,H}$	Elasticity of high-skilled employment to robot import shock	-0.0190	-0.0190
$\theta^{T,H}$	Elasticity of high-skilled employment to tool import shock	0.0475	0.0477
$\theta^{R,L}$	Elasticity of low-skilled employment to robot import shock	-0.3590	-0.3590
$\theta^{T,L}$	Elasticity of low-skilled employment to tool import shock	0.2270	0.2270

Description: This table presents the model's performance in matching the key moments: the elasticities of region–sector level high-skilled and low-skilled employment with respect to the imports of robots and tools.

Table C.5: **Parameters Estimated in the Model (Cont'd): Other Parameters**

Parameter	Para. Name	Value	Targeted Moments
	Production		
ξ^R	Decreasing return to scale parameter of robot investment goods production	0.0505	
ξ^T	Decreasing return to scale parameter of tool investment goods production	0.0529	Imports of robots and tools by region and sector
A_n^s	Region-sector level productivity	10.6702 (mean)	
μ_1^s	Sector-specific mean (across firms) high-skilled worker productivity	0.2157 (mean)	
μ_2^s	Sector-specific mean (across firms) robot productivity	−1.3304 (mean)	
σ_1^s	Sector-specific standard deviation (across firms) high-skilled worker productivity	1.0146 (mean)	Wage and employment of high-skilled and low-skilled workers by region and sector
σ_2^s	Sector-specific standard deviation (across firms) robot productivity	1.5477 (mean)	
ρ^s	Sector-specific correlation (across firms) between high-skilled worker productivity and robot productivity	0.0765 (mean)	
	Trade		
	Elasticity of domestic composite goods trade cost w.r.t.		
β^0	$\mathbf{1}(n'=n)$	−1.1094	
β^1	$\text{Contig}_{n'n}$	−1.0054	
β^2	$\log(\text{Dist to Coast}_n)$	−0.6190	
β^3	$\log(\text{Dist to Coast}_{n'})$	−0.1693	
β^4	$\mathbb{N}(\text{Ports})_n$	0.3855	
β^5	$\mathbb{N}(\text{Ports})_{n'}$	0.1583	
β^6	$\log(\text{Dist}_{n'n})$	0.5764	
β^7	$\text{Contig}_{n'n}\log(\text{U}^s)$	0.6008	
β^8	$\log(\text{Dist to Coast}_n)\log(\text{U}^s)$	0.5956	
β^9	$\log(\text{Dist to Coast}_{n'})\log(\text{U}^s)$	0.0584	
β^{10}	$\mathbb{N}(\text{Ports})_n\log(\text{U}^s)$	−0.5528	
β^{11}	$\mathbb{N}(\text{Ports})_{n'}\log(\text{U}^s)$	−0.1227	
β^{12}	$\log(\text{Dist}_{n'n})\log(\text{U}^s)$	−0.2250	
β^{13}	$\log(\text{U}^s)$	3.3709	Region-sector level imports
β^{14}	$\mathbf{1}(n'=n)\log(\text{U}^s)$	1.6955	
β^{15}	$\mathbf{1}(n'=n)\log(\text{high-skilled labor share}^s)$	−3.4660	
β^{16}	$\text{Contig}_{n'n}\log(\text{high-skilled labor share}^s)$	−3.3575	
β^{17}	$\log(\text{Dist to Coast}_n)\log(\text{high-skilled labor share}^s)$	−0.3025	
β^{18}	$\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s)$	−0.0936	
β^{19}	$\mathbb{N}(\text{Ports})_n\log(\text{high-skilled labor share}^s)$	0.0117	
β^{20}	$\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$	0.0653	
β^{21}	$\log(\text{high-skilled labor share}^s)$	−2.8436	
β^{22}	$\log(\text{Dist}_{n'n})\log(\text{high-skilled labor share}^s)$		
	Elasticity of imported composite goods trade cost w.r.t.		
β^{23}	$\log(\text{Dist to Coast}_{n'})$	0.0313	
β^{24}	$\mathbb{N}(\text{Ports})_{n'}$	−0.0271	
β^{25}	$\log(\text{Dist to Coast}_{n'})\log(\text{U}^s)$	0.0179	
β^{26}	$\mathbb{N}(\text{Ports})_{n'}\log(\text{U}^s)$	−0.00015	
β^{27}	$\log(\text{U}^s)$	0.7177	
β^{28}	$\mathbf{1}(\text{Imported})$	3.0806	
β^{29}	$\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s)$	0.1406	
β^{30}	$\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$	0.0028	
β^{31}	$\log(\text{Dist}_{n'n})\log(\text{high-skilled labor share}^s)$	0.2701	
β^{32}	$\log(\text{high-skilled labor share}^s)$	−0.8755	
	Elasticity of imported robot capital goods trade cost w.r.t.		
$\beta^{1,R}$	$\log(\text{Dist to Coast}_{n'})$	0.1272	
$\beta^{2,R}$	$\mathbb{N}(\text{Ports})_{n'}$	−0.3827	
$\beta^{3,R}$	$\log(\text{Dist to Coast}_{n'})\log(\text{U}^s)$	0.0360	
$\beta^{4,R}$	$\mathbb{N}(\text{Ports})_{n'}\log(\text{U}^s)$	0.2446	
$\beta^{5,R}$	$\log(\text{U}^s)$	0.2990	Imports of robot capital by region-sector
$\beta^{6,R}$	$\mathbf{1}(\text{Imported})$	3.3035	
$\beta^{7,R}$	$\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s)$	0.2522	
$\beta^{8,R}$	$\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$	−0.1113	
$\beta^{9,R}$	$\log(\text{high-skilled labor share}^s)$	0.1457	
	Elasticity of imported tool capital goods trade cost w.r.t.		
$\beta^{1,T}$	$\log(\text{Dist to Coast}_{n'})$	0.3861	
$\beta^{2,T}$	$\mathbb{N}(\text{Ports})_{n'}$	−0.2617	
$\beta^{3,T}$	$\log(\text{Dist to Coast}_{n'})\log(\text{U}^s)$	−0.2514	
$\beta^{4,T}$	$\mathbb{N}(\text{Ports})_{n'}\log(\text{U}^s)$	0.2733	
$\beta^{5,T}$	$\log(\text{U}^s)$	0.6267	Imports of tool capital by region-sector
$\beta^{6,T}$	$\mathbf{1}(\text{Imported})$	2.7747	
$\beta^{7,T}$	$\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s)$	0.2727	
$\beta^{8,T}$	$\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$	−0.0602	
$\beta^{9,T}$	$\log(\text{high-skilled labor share}^s)$	0.3065	
	Labor Migration		
$f^H/\text{mean}(w_n^{s,H})$	Fixed cost of becoming high-skilled workers (relative to high-skilled wage)	3.5484	Share of new workers who are high-skilled
	Elasticity of migration cost w.r.t.		
χ^0	$\mathbf{1}(n'=n)$	−7.6297	
χ^1	$\text{Contig}_{n'n}$	−6.5904	
χ^2	$\log(\text{Dist}_{n'n})$	2.0054	
χ^3	$\lvert\log(\text{U}^{s'})-\log(\text{U}^s)\rvert$	5.4627	
χ^4	$\text{Contig}_{n'n}\lvert\log(\text{U}^{s'})-\log(\text{U}^s)\rvert$	6.4620	Share of high-skilled workers moving from one region-sector to another region-sector
χ^5	$\log(\text{Dist}_{n'n})\lvert\log(\text{U}^{s'})-\log(\text{U}^s)\rvert$	3.3443	Share of low-skilled workers moving from one region-sector to another region-sector
χ^6	$\mathbf{1}(n'=n)\lvert\log(\text{U}^{s'})-\log(\text{U}^s)\rvert$	2.2070	
χ^7	$\lvert\text{high-skilled labor share}^{s\prime}-\text{high-skilled labor share}^s\rvert$	6.2657	
χ^8	$\text{Contig}_{n'n}\lvert\text{high-skilled labor share}^{s\prime}-\text{high-skilled labor share}^s\rvert$	5.1353	
χ^9	$\log(\text{Dist}_{n'n})\lvert\text{high-skilled labor share}^{s\prime}-\text{high-skilled labor share}^s\rvert$	0.7093	
χ^{10}	$\mathbf{1}(n'=n)\lvert\text{high-skilled labor share}^{s\prime}-\text{high-skilled labor share}^s\rvert$	1.3961	

Description: This table presents the model parameters that are estimated with the SMM method within the model and focuses on the parameters related to production, trade, and migration. We present the key parameters related to robot and tool technologies in Table 6.

C.6 Aggregate Statistics

Changes in employment of type $e \in \{H, L\}$ and total employment equal the following:

$$\text{dlog}(L^e) = \sum_{n=1}^{N}\sum_{s=1}^{S} \frac{l_{n,t_0}^{s,e}}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,e}}\,\text{dlog}(l_{n,t_0}^{s,e}),$$

and

$$\text{dlog}(L) = \frac{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,H}}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,H} + l_{n,t_0}^{s,L}}\,\text{dlog}(L^H) + \frac{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,L}}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,H} + l_{n,t_0}^{s,L}}\,\text{dlog}(L^L).$$

The skill premium at time t equals the following:

$$\text{Skill Premium} = \frac{\frac{1}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t}^{s,H}}\sum_{n=1}^{N}\sum_{s=1}^{S} w_{n,t}^{s,H} l_{n,t}^{s,H}}{\frac{1}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t}^{s,L}}\sum_{n=1}^{N}\sum_{s=1}^{S} w_{n,t}^{s,L} l_{n,t}^{s,L}}.$$

Average foreign price change for capital $l \in \{R, T\}$:

$$\text{Ave Price Chg. for } l = \sum_{n=1}^{N}\sum_{s=1}^{S} \frac{IMP_n^{s,l}}{\sum_{n=1}^{N}\sum_{s=1}^{S} IMP_n^{s,l}} \left(\text{dlog}(h_{n,N+1}^{s,l}) + \text{dlog}(t^{s,l})\right)$$

Average tariff for capital $l \in \{R, T\}$:

$$\text{Ave Tariff for } l = \sum_{n=1}^{N}\sum_{s=1}^{S} \frac{IMP_n^{s,l}}{\sum_{n=1}^{N}\sum_{s=1}^{S} IMP_n^{s,l}} \tau^{s,l}$$

The change in workers' welfare equals the weighted average of workers of both types from all regions and sectors:

$$\begin{aligned}
\text{dlog}\, v^{worker} &= \sum_{n=1}^{N}\sum_{s=1}^{S} \frac{l_{n,t_0}^{s,H}(v_{n,t}^{s,H} - v_{n,t_0}^{s,H}) + l_{n,t_0}^{s,L}(v_{n,t}^{s,L} - v_{n,t_0}^{s,L})}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,H} v_{n,t_0}^{s,H} + l_{n,t_0}^{s,L} v_{n,t_0}^{s,L}} \\
&= \sum_{n=1}^{N}\sum_{s=1}^{S} \frac{l_{n,t_0}^{s,H} v_{n,t_0}^{s,H}}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,H} v_{n,t_0}^{s,H} + l_{n,t_0}^{s,L} v_{n,t_0}^{s,L}} \frac{v_{n,t}^{s,H} - v_{n,t_0}^{s,H}}{v_{n,t_0}^{s,H}} \\
&+ \frac{l_{n,t_0}^{s,L} v_{n,t_0}^{s,L}}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,H} v_{n,t_0}^{s,H} + l_{n,t_0}^{s,L} v_{n,t_0}^{s,L}} \frac{v_{n,t}^{s,L} - v_{n,t_0}^{s,L}}{v_{n,t_0}^{s,L}}.
\end{aligned}$$

The change in national welfare equals the weighted average of workers of both types and capitalists from all regions and sectors:

$$\text{dlog}\, v^{national} = \sum_{n=1}^{N}\sum_{s=1}^{S} \frac{l_{n,t_0}^{s,H}(v_{n,t}^{s,H} - v_{n,t_0}^{s,H}) + l_{n,t_0}^{s,L}(v_{n,t}^{s,L} - v_{n,t_0}^{s,L}) + (v_{n,t}^{s,Cap,R} - v_{n,t_0}^{s,Cap,R}) + (v_{n,t}^{s,Cap,T} - v_{n,t_0}^{s,Cap,T})}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,H} v_{n,t_0}^{s,H} + l_{n,t_0}^{s,L} v_{n,t_0}^{s,L} + v_{n,t_0}^{s,Cap,R} + v_{n,t_0}^{s,Cap,T}},$$

where $v_{n,t_0}^{s,Cap,R}$ and $v_{n,t_0}^{s,Cap,T}$ denote the welfare (discounted utility) of robot and tool capitalists defined based on Equation (18).

According to the income approach, the country's normal GDP can be calculated by aggregating the wage bill, rental income, and profits generated by capitalists:

$$NGDP = \sum_{n=1}^{N} \sum_{s=1}^{S} w_n^{s,H} l_n^{s,H} + w_n^{s,L} l_n^{s,L} + (R_n^{s,R} K_n^{s,R} - \Sigma_n^{s,R} M_n^{s,R}) + (R_n^{s,T} K_n^{s,T} - \Sigma_n^{s,T} M_n^{s,T}).$$

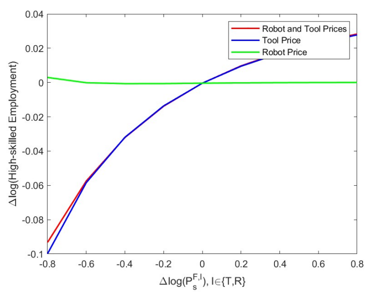
The change in real GDP measures the change in quantity, while prices remain the same. Therefore,

$$\begin{aligned} \text{dlog}(GDP) = \frac{1}{NGDP} \sum_{n=1}^{N} \sum_{s=1}^{S} & w_n^{s,H} l_n^{s,H} \, \text{dlog}(l_n^{s,H}) + w_n^{s,L} l_n^{s,L} \, \text{dlog}(l_n^{s,L}) \\ & + R_n^{s,R} K_n^{s,R} \, \text{dlog}(K_n^{s,R}) - \Sigma_n^{s,R} M_n^{s,R} \, \text{dlog}(M_n^{s,R}) \\ & + R_n^{s,T} K_n^{s,T} \, \text{dlog}(K_n^{s,T}) - \Sigma_n^{s,T} M_n^{s,T} \, \text{dlog}(M_n^{s,T}). \end{aligned}$$

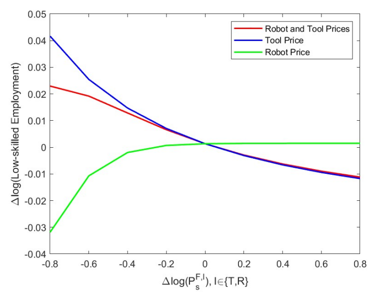
C.7 Other Results

Figure C.2: **Aggregate Effects of Robot and Tool Import Price Changes**

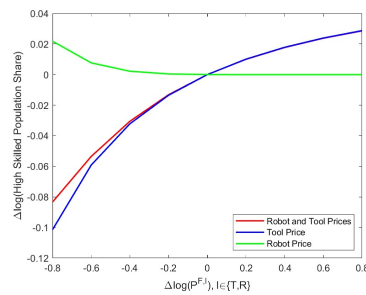
(a) High-skilled Employment



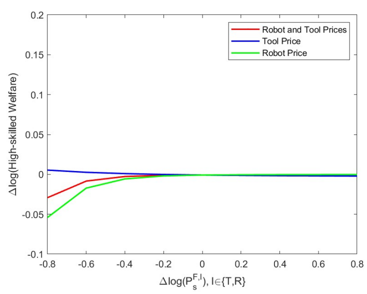
(b) Low-skilled Employment



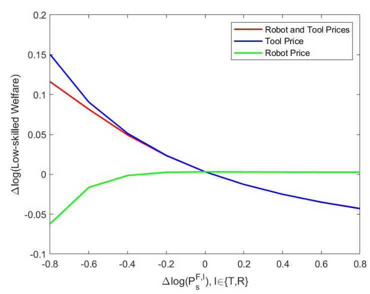
(c) High-skilled Population Share



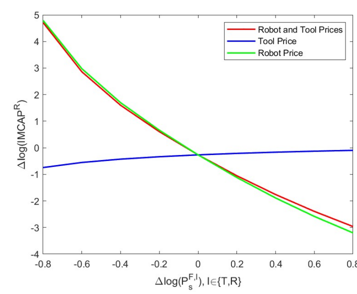
(d) High-skilled Worker Welfare



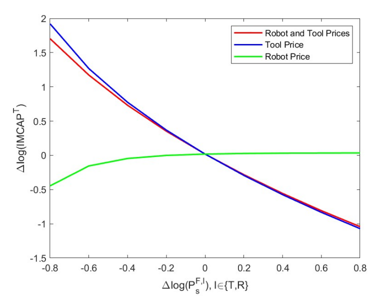
(e) Low-skilled Worker Welfare



(f) Robot Imports



(g) Tool Imports



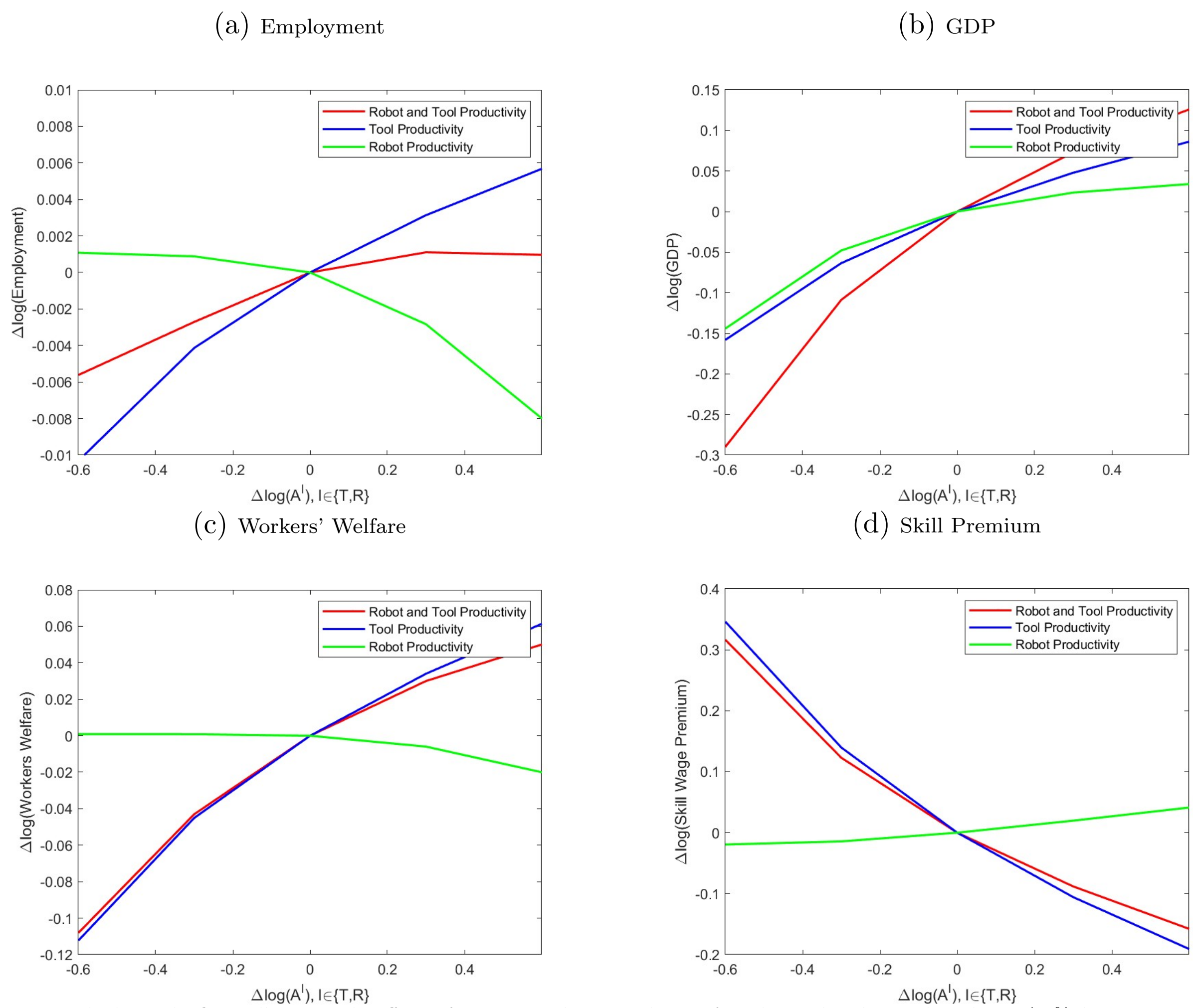
Description: The figure illustrates the effects of varying robot and tool import prices (80% decrease to 80% increase) on high-low-skilled employment, high-skilled population share, high-low-skilled welfare, and robot and tool imports, relative to the initial steady state (1997). Red lines represent simultaneous robot and tool price changes, blue lines represent tool-only changes, and green lines represent robot-only changes. Uniform price changes across all sectors are considered.

C.8 Effects of Capital Producers' Productivity Changes

Figure C.3a shows that a decrease in the productivity of robot producers or an increase in the productivity of tool producers can lead to a rise in aggregate employment. Enhancing the productivity of tool producers by 60% results in a 0.6% increase in employment, whereas raising the productivity of robot producers by 60% results in a 0.8% increase in employment.

Simultaneous productivity enhancements of a comparable magnitude for both robot and tool producers, can significantly boost GDP while having little effect on employment and a

Figure C.3: **Aggregate Effects of Robot and Tool Capital Producer Productivity Changes**

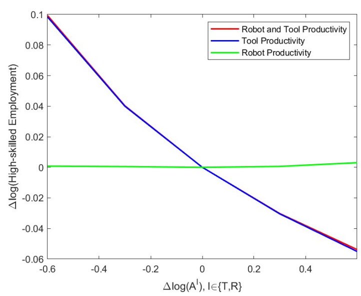


Description: The figure illustrates the effects of varying productivity changes for robot and tool capital producers (60% decrease to 60% increase) on aggregate employment, GDP, workers' welfare, and skill premium, relative to the initial steady state (1997). Red lines represent simultaneous robot and tool capital producer productivity changes, blue lines represent tool-only changes, and green lines represent robot-only changes. Uniform capital producer productivity changes across all regions and sectors are considered.

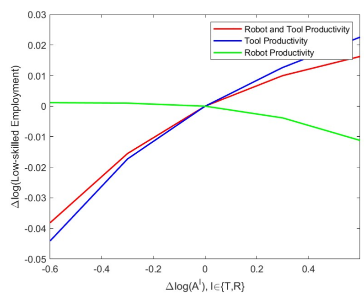
positive effect on workers' welfare. Figure C.3b shows that an increase in the productivity of either robot or tool producers can lead to a rise in GDP; a 60% increase in the productivity of both robot and tool producers results in a 30% growth in GDP. Similar to the employment effects, workers' welfare also increases with tool producers' productivity but decreases with robot producers' productivity (Figure C.3c). However, the improvement in tool technology has a much greater positive impact on workers' welfare compared to the negative effect of advancements in robot technology. Figure C.3d shows that an increase in the productivity of robot producers or a decrease in the productivity of tool producers can significantly increase the skill premium and inequality. Tool productivity changes can affect the skill premium more substantially compared to robot productivity changes. We present the effects of productivity changes for robot and tool capital producers on other aggregate outcomes in Figure C.4.

Figure C.4: **Aggregate Effects of Robot and Tool Capital Producer Productivity Changes**

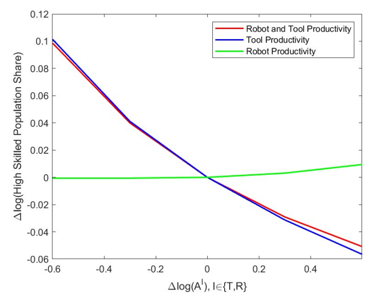
(a) High-skilled Employment



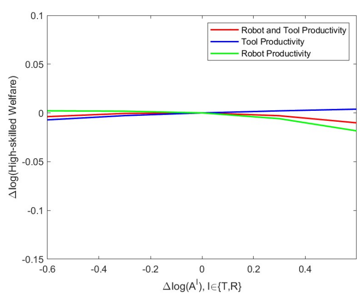
(b) Low-skilled Employment



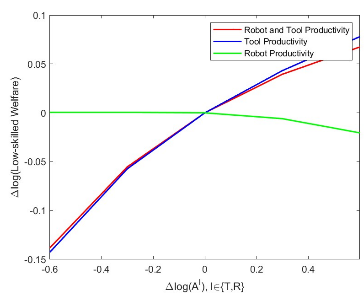
(c) High-skilled Population Share



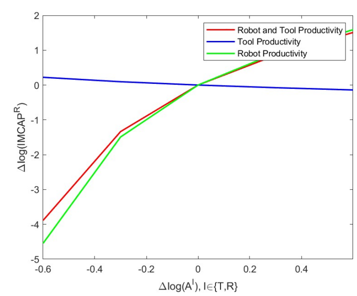
(d) High-skilled Worker Welfare



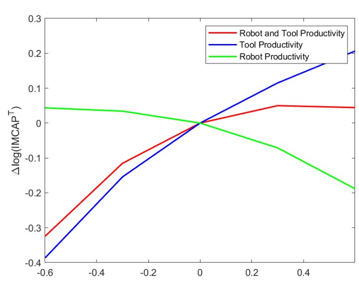
(e) Low-skilled Worker Welfare



(f) Robot Imports



(g) Tool Imports



Description: The figure illustrates the effects for varying productivity changes of robot and tool capital producers (60% decrease to 60% increase) on high-skilled/low-skilled employment, high-skilled population share, high-skilled welfare, low-skilled welfare, robot imports, and tool imports, relative to the initial steady state (1997). Red lines represent simultaneous robot and tool capital producer productivity changes, blue lines represent tool-only changes, and green lines represent robot-only changes. Uniform capital producer productivity changes across all regions and sectors are considered.

C.9 Effects of Capital Producers' Productivity Changes

In this section, we ask, if the government optimally imposes tariffs or import subsidies on robots and tools to achieve a policy objective (e.g., increasing welfare or reducing inequality), what are the aggregate effects of these policies? We are interested in three policy objectives:

maximizing (1) GDP, (2) welfare, and (3) minimizing the skill wage premium (inequality). To ensure that we find an interior solution, we require that the government has a balanced budget for these subsidies and tariffs. That is, the tariffs collected from robot and tool imports cannot exceed the subsidies paid for them. Hence, the government solves the following problem:

$$
\begin{aligned}
\max_{\tau_s^R, \tau_s^T} \ & \text{Obj} \in \{\text{GDP, Welfare, - Skill Wage Premium}\} \\
\text{s.t. } & \text{Equilibrium conditions (Equations C.11-C.19)} \\
& \sum_{n=1}^{N} \sum_{s=1}^{S} (IMP_n^{s,R} \tau^{s,R} + IMP_n^{s,T} \tau^{s,T}) \geq 0,
\end{aligned}
\tag{C.40}
$$

where $IMP_n^{s,R}$ denotes the (pre-tariff) imports of robots and $IMP_n^{s,T}$ denotes the (pre-tariff) imports of tools.